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Financial Frictions, Financial Shocks, and Aggregate Volatility

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Abstract

I revisit the Great Inflation and the Great Moderation. I document an *immoderation* in corporate balance sheet variables so that the Great Moderation is best described as a period of divergent patterns in volatilities for real, nominal and financial variables. A model with time-varying financial frictions and financial shocks allowing for structural breaks in the size of shocks and the institutional framework is estimated. The paper shows that *(i)* while the Great Inflation was driven by bad luck, the Great Moderation is mostly due to better institutions; *(ii)* the slowdown in credit spreads is driven by an easier access to credit, while a higher exposure to financial risk determines the *immoderation* of balance sheet variables; and *(iii)* financial shocks arise as relevant drivers of U.S. business cycle fluctuations.

JEL: E32, E44, C11, C13

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1 Introduction

Recent economic events suggest a strong interaction between the financial sector and aggregate business cycle fluctuations. While there has been a thorough study of the role played by the financial sector in propagating economic shocks originating in other sectors, the assessment of the importance of financial shocks as drivers of business cycle fluctuations and the documentation of the propagation mechanism of financial shocks are at early stages. In addition, although the sources of business cycle fluctuations in the real sector is a long-standing issue in macroeconomics, understanding the driving forces of financial aggregates has just started to receive attention. When analyzing the interaction of the financial and real sectors and the relative importance of financial shocks, researchers face an additional challenge: the *immoderation* in financial aggregates contemporary with the Great Moderation in real and nominal variables. In this paper, I aim to evaluate the ability of a state-of-the-art DSGE model with financial rigidities and financial shocks to account for the divergent patterns in volatility.

I start by revisiting the evidence on the two main empirical regularities characterizing recent U.S. economic history: the Great Inflation and the Great Moderation. The Great Inflation refers to the decade of large volatility in inflation and nominal interest rates that started in 1970. The Great Moderation refers to the observed slowdown in the volatility of real and nominal variables since the mid-1980s. I show that while the Great Inflation can be described homogeneously for all aggregate variables under analysis, the Great Moderation is more complex. Jermann and Quadrini (2006) provide evidence on the larger magnitude of fluctuations in equity payout and debt repurchases in the U.S. nonfinancial sector during the Great Moderation. I provide further evidence on an immoderation for balance sheet variables in the U.S. nonfinancial corporate sector since the mid-1980s, which is contemporaneous to a slowdown in the volatility of corporate spreads.

To address these patterns in aggregate volatility, I build a dynamic stochastic general equilibrium model with an explicit financial sector. In particular, following Christiano, Motto, and Rostagno (2003), I integrate the financial accelerator model of Bernanke, Gertler, and Gilchrist (1999, BGG hereafter) into a version of the standard Smets and Wouters (2007) paradigm. I quantify the relative role played by financial factors, economic shocks, and monetary policy in shaping the evolution of aggregate volatility. To do so, I estimate the model economy using Bayesian methods allowing for structural breaks in a subset of the parameter space. Given the goal of establishing the role played by the financial sector in aggregate volatility, I not only include financial variables in the observable set but also proceed to the estimation of the deep parameters of the financial accelerator. From posterior predictive checks, I conclude that while the Great Inflation was mostly due to bad luck, the smoother business cycle fluctuations since the mid-1980s are the result of higher flexibility in the financial system and a more proactive monetary authority. The immoderation in balance sheet variables is accounted for by larger financial shocks hitting the US economy.

I explore the role of financial shocks as sources of business cycle fluctuations by introducing two financial shocks into the model economy. In the financial accelerator model, the asymmetric information between borrowers and lenders implies that loans are extended at a premium over the risk-free rate. This external finance premium can be thought of as being driven by two channels: the balance sheet channel and the information channel. The balance sheet channel captures the dependence of external financing opportunities on the composition of firms' balance sheets. The information channel implies that the external finance premium is a positive function of the severity of the agency problem. I include financial shocks affecting those two channels. Exogenous shocks to the balance sheet channel are introduced in the form of wealth shocks. Shocks to the information channel are modeled as innovations affecting the parameter governing bankruptcy costs. While wealth shocks are included in many studies of the financial accelerator model, time variation in marginal bankruptcy costs has not been explored in the literature. I find that, although the relative role of shocks to marginal bankruptcy cost is smaller than the one played by wealth shocks, it is crucial to assume that the marginal bankruptcy cost is a drifting parameter in order to deliver empirically plausible dynamics in corporate credit spreads. Moreover, the dynamics in the smoothed marginal bankruptcy cost parameter mirror the evolution of empirical measures of financial stress.

From variance decompositions, I conclude that financial shocks play a significant role in shaping aggregate volatility: they are the main driver of the variance in financial variables, investment, and the nominal risk-free interest rate. In addition, they are a solid secondary driver of the variance in output, hours, and inflation. Financial shocks in the model economy provide a foundation for the reduced-form shocks to the marginal efficiency of investment proposed by Justiniano, Primiceri, and Tambalotti (2011). They studied two investment-specific technology shocks: one affecting the transformation of consumption into investment goods and another affecting the transformation of investment goods into capital. I incorporate the former by means of a price shifter affecting the relative price of investment with respect to consumption while the latter is linked to the two financial shocks. As in Justiniano, Primiceri, and Tambalotti (2011) and contrary to most of the contributions to the literature, the price shifter plays a small role. Therefore, not only are shocks that originate in the financial sector important drivers of the U.S. business cycle, but ignoring them translates into an overstatement of the role played by the standard investment-specific technology shock.

The institutional framework plays a determining role in shaping the relative contribution of financial shocks in driving business cycle fluctuations for nonfinancial variables. For example, if the dovish monetary policy regime of the 1970s had been in place during the Great Moderation, financial shocks would have accounted for 50% of the variance in inflation and 69% of the variance in the federal funds rate instead of 6% and 37%, respectively. If the conditions of access to credit during the post-1980s were identical to the ones characterizing the 1960s and 1970s, then financial shocks would have explained 66% of the variance of output and 88% of that in investment instead of the actual 16% and 40%, respectively. Thus, although the size of financial shocks has increased over time, their relative contribution to the variance of real variables has not increased dramatically thanks to the institutional changes implemented during the mid-1980s.

This paper relates to two strands of the empirical macroeconomic literature. The first strand addresses the study of the Great Moderation and the second one considers the estimation of the financial accelerator model. Since Kim and Nelson (1999) and McConnell and Pérez-Quirós (2000) dated the start of the Great Moderation, there has been a growing literature on dissecting the possible sources of such a mildness in business cycle fluctuations. Recently, Jermann and Quadrini (2006) and De Blas (2009) also explore the role played in the Great Moderation by changes in the financial rigidities faced by firms. I contribute to this strand of the literature by performing a thorough analysis of the evolution of financial variables, which leads me to document a broader empirical regularity on corporate balance sheet variables. The divergent pattern in financial volatility adds a layer of difficulty to macro models that attempt to account for the observed breaks in volatilities. Regarding the estimation of a DSGE model, including the financial accelerator, most of the contributions use post-1985 data in order to avoid the structural breaks linked to the Great Moderation. I address directly the issue of structural breaks while estimating the deep parameters of the financial accelerator. Therefore, the main contribution of this paper to the strand of the literature is to provide a data-based quantification of the size of the financial accelerator, to document its evolution over time, and to explore financial shocks.

The order of this paper is as follows. Section 2 presents the empirical evidence that motivates the paper. I describe the model in section 3. I describe the estimation procedure and report the estimation results in section 4. Section 5 analyzes the drivers of the divergent patterns in volatility. In section 6, I study the relative importance of each shock and the propagation of financial shocks. Section 7 concludes.

2 Empirical Evidence

I examine macroeconomic and financial data for the United States over the 1954-2006 period, which includes the Great Inflation and the Great Moderation. The data range covers only until 2006 to avoid distortions caused by nonlinearities induced by the zero lower bound on the federal funds rate, binding downward nominal rigidities and upward pressures on financial volatilities during the recent years.

Following McConnell and Pérez-Quirós (2000), I estimate the timing of the structural breaks in the residual variance of real and nominal variables by running an autoregressive model of order 1 with drift on the cyclical component of these variables. Assuming the error of the AR(1) model, ε_t, follows a normal distribution, I can ensure that $|\widehat{\varepsilon}_t|\sqrt{\pi/2}$ is an unbiased estimator for the residual standard deviation of the cyclical variable under analysis. Thus, I can perform Bai and Perron (1998) tests to estimate the dating and the number of breaks in the cyclical standard deviation. The results for these tests are reported in table 1. While for the volatility of nominal variables, I can reject the null of parameter constancy for two different dates, I can reject the null at only one date for real variables. Nominal variables clearly indicate 1970 as the starting point of the Great Inflation and the end of its aftermath in the early 1980s. The break in the volatility of real variables is also quite uniform, pointing to the second quarter of 1984 as the start of the Great Moderation. Moreover, when running Chow's (1960) tests using 1970:Q1 and 1984:Q2 as the breakpoints, I conclude that I can reject the null of parameter constancy at both dates for all variables under analysis. Therefore, by dividing up the sample into three subsamples, 1954:Q4-1969:Q4, 1970:Q1-1984:Q1, and 1984:Q2-2006:Q4, I am not misrepresenting the estimated breaks in cyclical volatilities. During the Great Inflation, the volatility of nominal variables more than doubles and that of real variables increases, on average, by 50%. The Great Moderation is characterized by a reduction in cyclical volatilities of about 55% for real variables and in between 50% and 60% for nominal variables.

Given the dating of the two empirical regularities, I analyze the evolution of the cyclical volatility of a comprehensive set of financial variables for the U.S. corporate sector. I incorporate two alternative measures of net worth based on balance sheet data: corporate net worth 1, which is defined as total assets minus total liabilities, and corporate net worth 2, which is equal to tangible assets minus credit market liabilities. I use these two measures of net worth to construct the corresponding measures of corporate leverage. I consider two measures of corporate debt flows: the net increase in credit market liabilities and the net increase in corporate bonds[1]. I also explore two standard corporate ratios: Tobin's q and equity q. Tobin's q is defined as the ratio of the sum of the market value of equities and liabilities to total assets, while equity q is defined as the ratio of the market value of corporate equities to corporate net worth (measure 1). Finally, I explore six corporate credit spreads: the spread between the Moody's seasoned Baa corporate bond yield and the triple-A yield, between the Aaa rate and the federal funds rate, between the Baa rate and the federal funds rate, between the prime lending rate and the federal funds rate, between the Aaa rate and the 10-year Treasury yield, and between the Baa rate and the 10-year Treasury yield.

As reported in table 2, balance-sheet variables have experienced a steady increase in volatility—which I will call *immoderation*—since the early 1970s. During the Great Inflation, the increase in cyclical volatility ranges from 14% for corporate net worth (measure 2) to more than triple for the two measures of corporate leverage. The volatility of the cyclical component of the Tobin's q and equity q ratios is about 30% larger. Corporate debt variability more than doubles during the 1970s, while the cyclical volatility of corporate bonds is 70% larger than in the previous decades. Since the mid 1980s, the volatility of the measures of corporate net worth almost doubles. The variability in corporate credit almost triples if defined using bonds and increases by 20% if we restrict our attention to credit-market liabilities. The cyclical volatility of Tobin's q increases by 16%, while the increase for the equity q ratio is almost 50%. Despite the diversity of relative sizes in the increases in cyclical volatility, we can argue that there is evidence of an immoderation in US corporate balance sheet variables not only during the Great Inflation, but also during the Great Moderation. As shown in the lower part of table 2, corporate credit spreads mimic quite closely the documented evolution in nominal variables as shown in table 1. Thus, their volatility increases dramatically during the Great Inflation and falls substantially during the Great Moderation.

[1] Christiano, Motto, and Rostagno (2014) define credit in the business sector as the credit market instruments component of net increase in liabilities for nonfarm, nonfinancial corporate business and nonfarm, noncorporate business. Levin, Natalucci, and Zakrajšek (2004) use firm-level bond data to construct an empirical counterpart to one-period debt contracts.

3 The Model

The theoretical framework features real and nominal rigidities as in Smets and Wouters (2007). In order to assess the role played by financial frictions in the evolution of volatilities in the U.S. economy, I extend the framework to include financial rigidities as in BGG. Financial frictions arise because there is asymmetric information between borrowers and lenders. Following Townsend's (1979) costly state verification framework, I assume that while borrowers freely observe the realization of their idiosyncratic risk, lenders must pay monitoring costs to observe an individual borrower's realized return.

Since Christiano, Motto, and Rostagno (2003) integrated the financial accelerator mechanism of BGG into the workhorse DSGE model, several studies have focused on assessing the empirical relevance of the financial accelerator by comparing the model fit with that of the standard DSGE model or on studying the propagation of real and nominal shocks. In this paper, I focus the analysis on two issues: *(i)* the role of financial shocks and *(ii)* the model's potential to account for breaks in the second moments of the data. I incorporate into the theoretical framework a shock to firms' net worth and a shock to agency costs. While the former has been previously studied, the inclusion of the latter is a novelty of this paper.

The model economy is populated by households, financial intermediaries, entrepreneurs, capital producers, intermediate good firms, retailers, labor packers, and government.

3.1 Retailers

The retail sector is populated by infinitely lived and perfectly competitive firms producing final goods, Y_t, by combining a continuum of intermediate goods, $Y_t(i)$, $i \in [0,1]$, according to a Dixit-Stiglitz aggregator:

$$Y_t = \left[\int_0^1 (Y_t(i))^{\frac{1}{1+\lambda_t^p}}\right]^{1+\lambda_t^p}.$$

As in Smets and Wouters (2007), the price markup, λ_t^p, is assumed to follow the exogenous stochastic process

$$\ln(\lambda_t^p) = (1-\rho_{\lambda_p})\ln(\lambda_\star^p) + \rho_{\lambda^p}\ln(\lambda_{t-1}^p) + \varepsilon_{\lambda_p,t} - \theta_p\varepsilon_{\lambda_p,t-1}, \tag{1}$$

where $\varepsilon_{\lambda_p,t} \sim \mathcal{N}(0,\sigma_{\lambda_p})$ and $\lambda_\star^p$ stands for the value of the markup in the steady state.

3.2 Intermediate goods sector

There is a continuum of infinitely lived producers of intermediate goods, indexed by $i \in [0,1]$, operating under monopolistic competition. They produce intermediate inputs, $Y_t(i)$, combining labor services, H_t, provided by households and capital services, k_t, provided by entrepreneurs using a Cobb-Douglas technology:

$$Y_t\left(i\right) = \left[Z_{a,t} H_t\left(i\right)\right]^{1-\alpha} k_t\left(i\right)^{\alpha} - Z_{a,t}\Phi, \tag{2}$$

where Φ is a fixed cost of production and $Z_{a,t}$ stands for the neutral technology shock. I assume that $Z_{a,t}$ is such that

$$Z_t \equiv \log\left(\Delta Z_{a,t}\right) = \left(1-\rho_z\right)\Upsilon_z + \rho_z Z_{t-1} + \varepsilon_{Z,t}, \qquad \epsilon_{Z,t} \sim \mathcal{N}\left(0, \sigma_Z\right) \tag{3}$$

Thus, I assume that the growth rate of the neutral technological progress follows an AR(1) process where Υ_z is the average growth rate of the economy.

Intermediate goods producers face a pricing problem in a sticky price framework à la Calvo. At any given period, a producer is allowed to reoptimize her price with probability $(1-\xi_p)$. I assume that those firms that do not reoptimize their prices set them using the following indexation rule:

$$P_t(i) = P_{t-1}(i)\pi_{t-1}^{\iota_p}\pi_{\star}^{1-\iota_p}, \tag{4}$$

where $\pi \equiv P_t/P_{t-1}$ is the gross inflation rate and $\pi_\star$ is the inflation rate in the steady state. When reoptimization is possible, an intermediate firm i will set the price $\widetilde{P}_t$ that maximizes the expected value of the firm as

$$\mathbb{E}_t \sum_{s=0}^{\infty} \xi_p^s \beta^s \frac{\Lambda_{t+s}}{\Lambda_t}\left[\widetilde{P}_t(i)\left(\prod_{l=1}^{s}\pi_{t+l-1}^{\iota_p}\pi_\star^{1-\iota_p}\right)Y_{t+s}(i) - W_{t+s}H_{t+s}(i) - P_{t+s}r_{t+s}^k k_{t+s}(i)\right], \tag{5}$$

subject to its demand function and to cost minimization. In the above expression, Λ_t stands for the stochastic discount factor between t and $t+s$ for households, W_t is the nominal wage, and r^k is the real rate paid on capital services.

3.3 Capital producers

Capital producers are infinitely lived agents operating in a perfectly competitive market. They produce new physical capital stock, K_{t+1}, using the following technology:

$$K_{t+1} = (1-\delta)K_t + \left[1 - \Phi\left(\frac{I_t}{I_{t-1}}\right)\right]\zeta_t I_t, \tag{6}$$

where the function $\Phi(\cdot)$ captures the existence of investment adjustment costs. We assume that $\Phi(\cdot)$ is an increasing and convex function such that in the steady state $\Phi(\cdot) = \Phi'(\cdot) = 0$ and $\Phi''(\cdot) \equiv \xi > 0$. The investment-specific technology shock, ζ_t, is assumed to evolve as

$$\ln(\zeta_t) = \rho_{\zeta,1}\ln(\zeta_{t-1}) + \varepsilon_{\zeta,t} \tag{7}$$

with $\varepsilon_{\zeta,t} \sim \mathcal{N}(\sigma_\zeta, 1)$.

3.4 Labor packers

As in Erceg, Henderson and Levin (2000), I assume that a representative labor packer or employment agency combines the differentiated labor services provided by households, $H_t(i)$, according to

$$H_t = \left[\int_0^1 H_t\left(i\right)^{\frac{1}{1+\lambda_t^w}}\right]^{1+\lambda_t^w},$$

where λ_t^w is the wage markup that evolves exogenously as

$$\ln(\lambda_t^w) = (1-\rho_{\lambda_w})\ln(\lambda_\star^w) + \rho_{\lambda_w}\ln(\lambda_{t-1}^w) + \varepsilon_{\lambda_w,t} - \theta_w\varepsilon_{\lambda_w,t-1} \tag{8}$$

with $\varepsilon_{\lambda_w,t} \sim \mathcal{N}(0, \sigma_{\lambda_w})$.

Profit maximization by perfectly competitive labor packers implies the following labor demand function:

$$H_t\left(i\right) = \left[\frac{W_t\left(i\right)}{W_t}\right]^{-\left(\frac{1+\lambda_t^w}{\lambda_t^w}\right)} H_t, \tag{9}$$

where $W_t(i)$ is the wage received from the labor packer by the type i household.

3.5 Households

I assume there is a continuum of infinitely lived households, each endowed with a specialized type of labor $i \in [0,1]$. Household i solves the following optimization problem:

$$\mathbb{E}_t \sum_{j=0}^{\infty} \beta^j b_{t+j} \left[\ln(C_{t+j} - hC_{t+j-1}) - \theta \frac{H_{t+j}(i)^{1+\nu}}{1+\nu} \right]$$

subject to

$$C_t + \frac{D_{t+1}}{P_t} + \frac{NB_{t+1}}{P_t} \quad \leq \quad \frac{W_t(i)}{P_t} H_t(i) + R_{t-1}\frac{D_t}{P_t} + R^n_{t-1}\frac{NB_t}{P_t} + div_t - T_t - Trans_t,$$

where C_t stands for consumption, h for the degree of habit formation, D_{t+1} for today's nominal deposits in the financial intermediary, $H_t(i)$ for hours worked, ν for the inverse of the Frisch elasticity of labor, b_t for a shock to the stochastic discount factor, R_t for the risk-free nominal interest rate paid on deposits, R^n_t for the risk-free nominal interest rate paid on government bonds, NB_t for nominal government bonds, T_t for real taxes (subsidies) paid to (received from) the government, div_t for dividends obtained from ownership of firms, and $Trans_t$ for wealth transfers to and from the entrepreneurial sector. The nature of these transfers is described later in this section. Following Erceg, Henderson, and Levin (2000), I assume complete markets, which implies that, in equilibrium, all households make the same choice of consumption, deposit holdings, and nominal bond holdings. Hours worked and wages differ across households because of the monopolistic labor supply.

The stochastic discount factor fluctuates endogenously with consumption and exogenously with the intertemporal preferece shock, b_t, which is given by

$$\ln(b_t) = \rho_b \ln(b_{t-1}) + \varepsilon_{b,t}, \quad \varepsilon_{b,t} \sim \mathcal{N}(0, \sigma_b). \tag{10}$$

Households set nominal wages for specialized labor services by means of staggered contracts. In any period t, a fraction ξ_p of households cannot reoptimize their wages, but they follow the indexation rule

$$W_t(i) = W_{t-1}(i) \left(\pi_{t-1}\mathfrak{z}_{t-1}\right)^{\iota_w} \left(\pi_\star \mathfrak{z}_\star\right)^{1-\iota_w}. \tag{11}$$

A fraction $(1-\xi_w)$ of households are allowed to choose an optimal nominal wage $\overline{W}_t(i)$, by solving

$$\max \mathbb{E}_t \sum_{s=0}^{\infty} \xi_w^s \beta^s \left[-b_{t+s}\theta \frac{H_{t+s}(i)^{1+\nu}}{1+\nu} + \Lambda_{t+s} W_t(j) H_{t+s}(j) \right],$$

subject to the labor demand function.

3.6 Entrepreneurs and financial intermediaries

Entrepreneurs are finitely lived risk-neutral agents who borrow funds captured by financial intermediaries from households. Conditional on survival, an entrepreneur j purchases physical capital, K_{t+1}^j, at relative price Q_t.

At the beginning of the period, an entrepreneur is hit by an idiosyncratic shock, ω_t^j, that affects the productivity of her capital holdings. This idiosyncratic shock is at the center of the informational asymmetry, as it is only freely observed by the entrepreneur. For tractability purposes, I assume ω_t^j, for all j, is *i.i.d* lognormal with *c.d.f.* $F(\omega)$ and parameters μ_ω and σ_ω, such that $\mathbb{E}[\omega^j] = 1$. After observing the realization of the idiosyncratic shock, entrepreneurs choose the capital utilization rate, u_t^j, that solves the following optimization problem

$$\max_{u_t^j} \left[u_t^j r_t^{k,j} - a\left(u_t^j\right) \right] \omega_t^j K_t^j, \tag{12}$$

where, around the steady state, $a(\cdot) = 0, a'(\cdot) > 0, a''(\cdot) > 0$ and $u^\star = 1$. Therefore, capital services, k_t^j, rented to intermediate goods producers are given by $k_t^j = u_t^j \omega_t^j K_t^j$.

The capital demand for entrepreneur j is given by the gross nominal return on holding one unit of capital from t to $t+1$

$$R_{t+1}^{k,j} = \left[\frac{r_{t+1}^{k,j} u_{t+1}^j + \omega_{t+1}^j (1-\delta) Q_{t+1}}{Q_t} \right] \frac{P_{t+1}}{P_t}, \tag{13}$$

where $\omega_{t+1}^j(1-\delta)Q_{t+1}$ is the return to selling the undepreciated capital stock back to capital producers.

An entrepreneur can finance the purchase of new physical capital by investing her own net worth, N_{t+1}^j, and using external financing (in nominal terms), B_{t+1}^j, to leverage her project. Given that the entrepreneur is risk neutral, she offers a debt contract that ensures the lender a return free of aggregate risk. The lender can diversify idiosyncratic risks by holding a perfectly diversified portfolio, which allows her to offer a risk-free rate on deposits to households. Financial intermediaries cannot observe the realized return of a borrower unless they pay an auditing cost. To minimize costs, lenders will audit borrowers only when they report their inability to repay the loan under the terms of the contract. A debt contract is characterized by a triplet consisting of the amount of the loan, B^j_{t+1}, the contractual rate, Z^j_{t+1}, and a schedule of state-contingent threshold values of the idiosyncratic shock, $\bar{\omega}^j_{n,t+1}$, where n refers to the state of nature. For values of the idiosyncratic productivity shock above the threshold, the entrepreneur is able to repay the lender at the contractual rate. For values below the threshold, the borrower defaults, and the lender steps in and seizes the firm's assets. A fraction of the realized entrepreneurial revenue, μ, is lost in the process of liquidating the firm. In this case, the financial intermediary obtains

$$(1-\mu_{t+1})P_t\omega^j_{n,t+1}R^k_{n,t+1}Q_tK^j_{t+1}, \tag{14}$$

where μ_{t+1} stands for the marginal bankruptcy cost. In the literature, the marginal bankruptcy cost is assumed to be a constant parameter. I assume, however, that it is a drifting parameter so that exogenous changes in the level of financial rigidities affect the business cycle properties of the model. Later in this section, I describe in detail the relevance of this assumption and the stochastic specification chosen.

The terms of the debt contract are chosen to maximize expected entrepreneurial profits conditional on the return of the lender, for each possible state of nature, being equal to the riskless rate. That is, the participation constraint is given by the zero profit condition for the financial intermediary from which I can derive the supply for loans:

$$\mathbb{E}_t\frac{R^k_{t+1}}{R_t}\left[\Gamma(\bar{\omega}_{t+1})-\mu_{t+1}G(\bar{\omega}_{t+1})\right]=\left(\frac{Q_tK_{t+1}-N_{t+1}}{Q_tK_{t+1}}\right), \tag{15}$$

where

$$\Gamma(\bar{\omega}^j_{t+1})=\int_0^{\bar{\omega}^j_{t+1}}\omega f(\omega)d\omega+\bar{\omega}_t\int_{\bar{\omega}^j_{t+1}}^{\infty}f(\omega)d\omega$$

is the expected share of gross entrepreneurial earnings going to the lender, and

$$\mu_{t+1}G(\bar{\omega}^j_{t+1})=\mu_{t+1}\int_0^{\bar{\omega}^j_{t+1}}\omega f(\omega)d\omega$$

is the expected monitoring costs. Equation (15) states that financial intermediaries are only willing to provide funds to entrepreneurs if they are compensated by the default risk. That is, lenders charge a premium over the risk-free rate, the so-called external finance premium,

$\mathbb{E}\left[R^k_{t+1}/R_t\right]$. Equation (15) provides one of the foundations of the financial accelerator mechanism: a linkage between the entrepreneur's financial position and the cost of external funds, which ultimately affects the demand for capital.

The external finance premium can be thought of as determined by two channels: the *balance sheet channel*, through the debt-to-assets ratio $\left(\frac{Q_t K_{t+1} - N_{t+1}}{Q_t K_{t+1}}\right)$, and the *information channel*, through the elasticity of the external finance premium with respect to the leverage ratio $\left(\frac{1}{\Gamma(\bar{\omega}_{t+1}) - \mu_{t+1} G(\bar{\omega}_{t+1})}\right)$. The external finance premium is the key relationship of the financial accelerator, as it determines the efficiency of the contractual relationship between borrowers and lenders. I enrich the theoretical framework by assuming that this essential mechanism is affected exogenously by two financial shocks: a wealth shock and a shock to the marginal bankruptcy cost.

The *balance sheet channel* states the negative dependence of the premium on the amount of collateralized net worth, N_{t+1}. The higher the stake of a borrower in the project, the lower the premium over the risk-free rate required by the intermediary. As discussed in detail below, I introduce shocks to this channel through an entrepreneurial equity shifter. These types of wealth shocks were first introduced by Gilchrist and Leahy (2002). Recently, they have been explored by Christiano, Motto, and Rostagno (2010); Nolan and Thoenissen (2009); and Gilchrist, Ortiz and Zakrajšek (2009).

Dib (2010) has explored shocks to the elasticity of the risk premium with respect to the entrepreneurial leverage ratio. He solves the model discarding the contribution of the dynamics of the idiosyncratic productivity threshold to the dynamics of the remaining variables.[2] Hence, those shocks can refer to shocks to the standard deviation of the entrepreneurial distribution, to agency costs paid by financial intermediaries to monitor entrepreneurs, and/or to the entrepreneurial default threshold. He cannot, however, discriminate among the sources of the shock. Christiano, Motto, and Rostagno (2010) solve the model completely so that they can introduce a specific type of shock affecting the efficiency of the lending activity. In particular, they propose riskiness shocks affecting the standard deviation of the entrepreneurial distribution. A positive shock to the volatility of the idiosyncratic productivity shock widens the distribution so that financial intermediaries find it more difficult to distinguish the quality of entrepreneurs. They explore further the role played by these risk shocks in Christiano, Motto, and Rostagno(2014), where they assume that risk shocks are similar to news shocks in the sense of having anticipated and unanticipated components embedded in the shock

[2]BGG perform simulation exercises under a parameterization that implies a negligible contribution of the dynamics of the cutoff. However, most of the contributions to the financial accelerator literature have adopted this result as a feature of the model, so they set those dynamics to zero.

specification. They conclude that risk shocks are the main driver of the US business cycle, with the anticipated component (signals) playing a predominant role.

I am interested in exploring the role of fluctuations in the conditions of access to credit in driving economic activity at business cycle frequencies. In the model, the marginal bankruptcy cost is the summary statistic for the level of the financial rigidity—that is, for the conditions of access to corporate credit. Thus, I introduce exogenous disturbances affecting the elasticity of the premium with respect to the leverage ratio by assuming that the marginal bankruptcy cost is time-variant. The information channel establishes that the external finance premium is a positive function of the severity of the agency problem measured by the marginal bankruptcy cost, μ_t. An increase in the level of financial rigidity implies an enlargement of the informational asymmetry rents, which translates into a higher premium on external funds. To the best of my knowledge, only Levin, Natalucci, and Zakrajšek (2004) have explored time variation along this margin. They estimate a partial equilibrium version of the BGG model using a panel of 900 U.S. nonfinancial firms over the period from 1997:1 to 2003:3. They find evidence of significant time variation in the marginal bankruptcy cost. In particular, they conclude that time variation in the parameter of interest is the main driver of the swings in the model-implied external finance premium.

I assume that the marginal bankruptcy cost evolves as follows

$$\mu_t = \frac{1}{1+e^{\varphi_t}} \tag{16}$$

$$\ln(\varphi_t) = (1-\rho_\varphi)\ln(\varphi_\star) + \rho_\varphi \ln(\varphi_{t-1}) + \varepsilon_{\varphi,t}, \quad \varepsilon_{\varphi,t} \sim \mathcal{N}(0,\sigma_\varphi), \tag{17}$$

where φ_t is shock to the marginal bankruptcy cost. This specification ensures that the realization of the marginal bankruptcy cost, μ_t, lies between 0 and 1 every period.[3] The unconditional mean of the process governing the agency problem between borrowers and lenders, $\mu^\star = 1/(1+e^{\varphi_\star})$, determines the average level of financial rigidity in the model economy. This parameter governs the size of the financial accelerator. In particular, $\mu^\star$ stands for the steady-state level of the marginal bankruptcy cost.

The other main component of the financial accelerator is the evolution of entrepreneurial wealth. Note that the return on capital and, hence, the demand for capital by entrepreneurs depend on the dynamics of net worth. Let V_t be entrepreneurial equity and W_t^e be the wealth transfers made by exiting firms to the pool of active firms. Then, aggregate entrepreneurial

[3] Alternatively, time variation in the marginal bankruptcy cost can be modeled as $\ln \mu_t = (1-\rho_\mu)\ln \mu_\star + \rho_\mu \ln \mu_{t-1} + \sigma_\mu \epsilon_\mu$, which does not restrict the realization of the marginal bankruptcy cost to lie in the unit interval. However, the posterior odds favor the restricted specification over the unrestricted one.

net worth (average net worth across entrepreneurs) is given by the following differential equation

$$\begin{aligned} P_t N_{t+1} &= x_t \gamma V_t + P_t W_t^e \\ &= x_t \gamma \left[P_{t-1} R_t^k Q_{t-1} K_t - R_{t-1} B_t - \mu_t G\left(\bar{\omega}_t\right) P_{t-1} R_t^k Q_{t-1} K_t \right] + P_t W_t^e, \end{aligned}$$

where γ is the survival probability, $\left[R_t^k P_{t-1} Q_{t-1} K_t^j - R_{t-1} B_t\right]$ is the nominal gross return on capital net of repayment of loans in the nondefault case, $\mu_t G\left(\bar{\omega}_t\right) R_t^k Q_{t-1} K_t$ is the gross return lost in case of bankruptcy, and x_t is the wealth shock, which is assumed to be

$$\ln(x_t) = \rho_x \ln(x_{t-1}) + \varepsilon_{x,t}, \quad \varepsilon_{x,t} \sim \mathcal{N}(0, \sigma_x). \tag{18}$$

Exogenously driven changes in the valuation of entrepreneurial equity need to be financed by another sector of the model economy. I assume that the household sector receives (provides) wealth transfers from (to) the entrepreneurial sector, which are defined as

$$Trans_t = N_{t+1} - \gamma V_t - W_t^e = \gamma V_t \left(x_t - 1\right), \tag{19}$$

where $\gamma V_t + W_t^e$ is the value that entrepreneurial equity would have taken if there were no wealth shocks.

3.7 Government

Government spending is financed by government nominal bonds sold to households and by lump-sum taxes:

$$NB_{t+1} + P_t T_t = P_t G_t + R_{t-1}^n NB_t, \tag{20}$$

where the process for public spending G_t is given by $G_t = \left(1 - \frac{1}{g_t}\right) Y_t$, where the government spending shock, g_t, follows the stochastic process:

$$\ln g_t = (1 - \rho_g) \ln g + \rho_g \ln g_{t-1} + \varepsilon_{g,t}, \;\; \varepsilon_{g,t} \sim \mathcal{N}(0, \sigma_g).$$

The monetary authority follows a Taylor-type interest rate rule. I assume that the authority adjusts the short-term nominal interest rate in response to deviations of inflation and output growth from the target—that is, their steady-state values:

$$\left(\frac{R_t^n}{R^{n\star}}\right) = \left(\frac{R_{t-1}^n}{R^{n\star}}\right)^{\rho_R} \left(\frac{\pi_t}{\pi^\star}\right)^{(1-\rho_R)\psi_\pi} \left(\frac{\Delta Y_t}{\Upsilon_z}\right)^{(1-\rho_R)\psi_y} e^{\eta_{mp}} \tag{21}$$

with $\rho_R > 0, (1-\rho_R)\psi_\pi > 0$, $(1-\rho_R)\psi_y > 0$, and

$$\eta_{mp,t} = \rho_{mp}\eta_{mp,t-1} + \varepsilon_{R,t}, \;\; \varepsilon_{R,t} \sim \mathcal{N}(0, \sigma_R). \tag{22}$$

4 Bayesian Inference

4.1 Data

I estimate the model with Bayesian estimation techniques using nine macroeconomic quarterly U.S. time series as observable variables: the growth rate of real per-capita net worth in the nonfarm business sector defined as tangible assets minus credit market liabilities, the growth rate of real per-capita gross value added (GVA) by the nonfarm business sector, the growth rate of real per-capita consumption defined as consumption of nondurables and services, the growth rate of real per-capita investment defined as gross private investment, the growth rate of real hourly wages in the nonfarm business sector, log hours worked, the log difference of the GVA deflator, the federal funds rate, and the spread between the Baa corporate bond rate and the 10-year US government bond rate. A complete description of the data set is given in the appendix. The model is estimated over the full sample period from 1954:Q4 to 2006:Q4.

4.2 Structural breaks

I aim to test the relative role played by three hypotheses in accounting for the observed breaks in volatilities: luck, the conduct of monetary policy, and financial institutions. To do so, I allow for breaks in three subsets of parameters: size of shocks, monetary policy coefficients, and the unconditional mean of the marginal bankruptcy cost, which characterizes the financial system. I perform the estimation exercise using the full sample information to estimate the parameters that are constant across subsamples and the corresponding subsample information to estimate those parameters that are subject to structural breaks. I use a relatively naïve approach in treating structural breaks since I assume economic agents do not face an inference problem to learn endogenously about the regimes. When forming rational expectations about the dynamic economy, they take regime changes as completely exogenous events and assume that the current regime will last forever. Thus, once a structural break in parameters happens, agents learn about it immediately and conveniently readjust their choices. This simplifying assumption facilitates the estimation when, as in this case, breaks in the steady state of the economy are allowed. However, the econometrician must make sure she is using the same information set as the economic agent when conducting the estimation exercise.

4.2.1 A simple example

Let us consider an AR(1) process with a time-varying mean:

$$x_t = \rho x_{t-1} + (1-\rho)\,\bar{x}_t + u_t, \tag{23}$$

where $|\rho| < 1$, $\bar{x}_t$ is the time-varying mean, and u_t is a zero-mean iid process. Let us define $\widetilde{x}_t = x_t - \bar{x}_t$—that is, the deviation of x_t with respect to the time-t mean of the process. Note that expression (23) cannot be written as

$$\widetilde{x}_t = \rho \widetilde{x}_{t-1} + u_t$$

as $\widetilde{x}_{t-1} \neq x_{t-1} - \bar{x}_t$. Instead, the model can be expressed as

$$\begin{aligned} x_t - \bar{x}_t &= \rho\,(x_{t-1} - \bar{x}_{t-1}) + \rho\,(\bar{x}_{t-1} - \bar{x}_t) + u_t \\ \widetilde{x}_t &= \rho \widetilde{x}_{t-1} + \rho\,(\bar{x}_{t-1} - \bar{x}_t) + u_t \end{aligned}$$

where $\widetilde{x}_t = x_t - \bar{x}_t$ and $\widetilde{x}_{t-1} = x_{t-1} - \bar{x}_{t-1}$.

To illustrate the relevant case for this paper, let us assume that the time-varying mean process is given by

$$\bar{x}_t = \begin{cases} \bar{x}_1 & \text{for } t < t^{\star} \\ \bar{x}_2 & \text{for } t \geq t^{\star} \end{cases} \tag{24}$$

Thus, we can represent (23) as follows:

- For $t < t_{\star}$, $\widetilde{x}_t = \rho \widetilde{x}_{t-1} + u_t$ where $\widetilde{x}_t = x_t - \bar{x}_1$ and $\widetilde{x}_{t-1} = x_{t-1} - \bar{x}_1$.

- For $t = t_{\star}$, $\widetilde{x}_t = \rho \widetilde{x}_{t-1} + \rho\,(\bar{x}_1 - \bar{x}_2) + u_t$ where $\widetilde{x}_t = x_t - \bar{x}_2$ and $\widetilde{x}_{t-1} = x_{t-1} - \bar{x}_1$.

- For $t > t_\star$, $\widetilde{x}_t = \rho \widetilde{x}_{t-1} + u_t$ where $\widetilde{x}_t = x_t - \bar{x}_2$ and $\widetilde{x}_{t-1} = x_{t-1} - \bar{x}_2$.

That is,

$$\begin{array}{rcll} (x_t - \bar{x}_1) & = & \rho\left(x_{t-1} - \bar{x}_1\right) + u_t, & \text{if } t < t_\star, \\ (x_t - \bar{x}_2) & = & \rho\left(x_{t-1} - \bar{x}_1\right) + \rho\left(\bar{x}_1 - \bar{x}_2\right) + u_t, & \text{if } t = t_\star, \text{and} \\ (x_t - \bar{x}_2) & = & \rho\left(x_{t-1} - \bar{x}_2\right) + u_t, & \text{if } t > t_\star. \end{array}$$

4.2.2 The DSGE model

Let ϱ be the subvector of structural parameters that is constant across subsamples and τ_t be the subvector subject to structural breaks. The system of log-linearized equilibrium conditions can be represented as

$$\Gamma_0\left(\varrho, \tau_t\right) \widetilde{s}_t = \Gamma_1\left(\varrho, \tau_t\right) \widetilde{s}_{t-1} + \Psi\left(\varrho, \tau_t\right) \varepsilon_t + \Pi\left(\varrho, \tau_t\right) \eta_t, \tag{25}$$

where $\widetilde{s}_t$ is a vector of model variables expressed in deviations from the steady state, ε_t is a vector of exogenous shocks, and η_t is a vector of rational expectations errors with elements $\eta_t^x = \widetilde{x}_t - \mathbb{E}_{t-1}\left[\widetilde{x}_t\right]$. As in the AR(1) example, $\widetilde{s}_t$ is in log-deviations from $\bar{s}_t$ and $\widetilde{s}_{t-1}$ from $\bar{s}_{t-1}$. The state-space representation of the solution to the LRE model can be written as follows:

$$\begin{array}{rl} \textit{Transition equations}: & \left[s_t - \bar{s}_t\right] = \Phi(\varrho, \tau_t)\left[s_{t-1} - \bar{s}_{t-1}\right] + \Phi_\varepsilon(\varrho, \tau_t)\varepsilon_t \text{and} \\ \textit{Measurement equations}: & y_t = B s_t, \end{array}$$

where s_t is the state vector in log-levels. Note that while breaks in the size of shocks shift only $\Phi_\varepsilon(\varrho, \tau_t)$ and breaks in monetary policy coefficients affect $\Phi(\varrho, \tau_t)$, breaks in parameters defining the steady state of the economy translate into changes in $\Phi(\varrho, \tau_t)$ and $\bar{s}$. To evaluate the likelihood function, we only need to modify the forecasting step of the Kalman filter to accommodate for structural breaks as follows:

$$\begin{array}{rcll} \left[\widehat{s}_{t|t-1} - \bar{s}_1\right] & = & \Phi\left(\varrho, \tau_1\right)\left[\widehat{s}_{t-1|t-1} - \bar{s}_1\right] & \text{if } t < t_\star \\ \left[\widehat{s}_{t|t-1} - \bar{s}_2\right] & = & \Phi\left(\varrho, \tau_2\right)\left[\bar{s}_1 - \bar{s}_2\right] + \Phi\left(\varrho, \tau_2\right)\left[\widehat{s}_{t-1|t-1} - \bar{s}_1\right] & \text{if } t = t_\star \\ \left[\widehat{s}_{t|t-1} - \bar{s}_2\right] & = & \Phi\left(\varrho, \tau_2\right)\left[\widehat{s}_{t-1|t-1} - \bar{s}_2\right] & \text{if } t > t_\star. \end{array}$$

4.3 Prior distribution

The prior information on the parameters used in the estimation exercise is available in the first three columns of tables 3 and 4. The parameter space can be partitioned into three sets. The first set contains the *fixed parameters*. I set the depreciation rate δ to 2.5%, the steady-state value of the government spending to output ratio is equal to 20%, and the steady-state values of the price and wage markup are fixed to 20%. I set the default probability, $F(\bar{\omega})$, equal to the average of the historical default rates for U.S. corporate bonds over the 1971–2005 period reported by Altman and Pasternack (2006). It is well-known that DSGE models have difficulties in matching sample averages of observable variables, which may distort the inference about the parameters governing model dynamics. To overcome this difficulty, I set the steady-state value of log-hours, $ln(H_\star)$, and the quarterly growth rate in the model economy, Υ.

The second set of parameters contains those estimated using the *full sample information*. These parameters are reported in the lower panel of table 3. *Parameters subject to structural breaks* are collected in the third set of parameters and shown in table 4. The priors are assumed to be identical across subsamples. My choices for standard parameters are along the lines of those in the recent literature. I provide a further description of the prior choice for the parameters governing the financial accelerator because there have been just a few attempts to estimate them.

I choose a Beta distribution for the survival probability, γ. The location parameter is chosen by solving the steady state for the financial sector when the debt-to-wealth ratio is equal to its historical average. This prior value implies that firms live, on average, 17 years, close to the median tenure reported by Levin, Natalucci, and Zakrajšek (2004) from a panel of 900 nonfinancial firms. I impose an inverted-Gamma distribution as the prior for σ_ω^2 with a location parameter of 0.16 and 4 degrees of freedom. For the steady-state value of the marginal bankruptcy cost, $\mu^\star$, I choose a Beta distribution for this parameter as it must lie inside the unit interval. For the location parameter of the Beta prior distribution, I consider micro evidence on bankruptcy costs. Altman (1984), using data from 26 firms, concludes that bankruptcy costs are about 20% of the firm's value prior to bankruptcy and in the range of 11% to 17% of a firm's value up to three years prior to bankruptcy. Alderson and Betker (1995) analyze 201 firms that completed Chapter 11 bankruptcies during the 1982–1993 period to determine that the mean liquidation costs are 36.5%. Using those two results, Carlstrom and Fuerst (1997) conclude that the interval empirically relevant for the marginal bankruptcy cost parameter is $[0.20, 0.37]$. Levin, Natalucci, and Zakrajšek (2004) estimate a partial equilibrium version of the model by BGG using panel data over the period from 1997 to 2003. As a byproduct of their estimation, they obtain the model-implied time series for the marginal bankruptcy cost. Their estimates lie in the range of 7% to 45%. Therefore, I assume that the Beta distribution for the unconditional average level of financial rigidity is centered at 0.30. I choose the diffusion parameter to be equal to 0.05 so that the 95% credible set encompasses most of the values provided in the literature.

4.4 Posterior estimates of the parameters

The last two columns of tables 3 and 4 report the posterior median and the 95% credible intervals of a chain of 500,000 posterior draws with a burn-in period of 20%.[4] I first analyze table 3, which contains those parameters not allowed to change over time. My estimates for standard parameters in DSGE models are along the lines of the estimates available in the literature. The only exception is the investment adjustment cost parameter, ξ, whose posterior median is 0.61. This relatively low value for the adjustment cost parameter suffices to put discipline in investment dynamics, given that the model-implied volatility in investment at business cycle fluctuations is similar to the observed one. I finalize the discussion on the parameters estimated on the full data information by considering the two parameters linked to the financial rigidity: the survival probability of entrepreneurs, γ, and the variance in the idiosyncratic productivity shock, σ_{ω}^2. The survival probability of entrepreneurs is estimated to be about 98% per quarter which implies a median life for entrepreneurs of about 12 years. This value is very close to the values used in the literature: Bernanke, Gertler, and Gilchrist (1999) set $\gamma = 0.973$; Christiano, Motto, and Rostagno (2010) propose $\gamma = 0.9762$; and Christiano, Motto, and Rostagno (2014) use $\gamma = 0.985$. The variance of the idiosyncratic productivity shock is estimated to be equal to 0.30, similar to the 0.24 value set by Christiano, Motto, and Rostagno (2010).

Table 4 reports the estimates for those parameters allowed to change in 1970:Q1 and 1984:Q2. First, I analyze the estimated breaks in the *parameters governing the conduct of monetary policy*. As pointed out elsewhere in the literature, the response of the monetary authority to inflation is looser in the 1970s than in the 1950s-1960s and the Great Moderation. In particular, during the Burns-Miller tenure, the response to inflation was about 15% milder than in Martin's mandate. The Volcker-Greenspan period is characterized by a tight response to inflation, which is about 65% larger than during the Great Inflation. The response of the

[4] I have generated two additional chains of 400,000 posterior draws. The results reported across chains are almost identical.

monetary authority to the real side of the economy has steadily been tighter over time, so that during the Great Moderation the response to deviations of output growth from the target is twice as large as the response during the '50s and '60s.

Next, I consider the *parameter characterizing the conditions of access to credit*. The unconditional mean of the marginal bankruptcy cost, which accounts for the easiness of access to external financing, does not change significantly during the Great Inflation. While before the Great Moderation financial intermediaries were able to recover 90% of the value of the firm in the event of bankruptcy, the recovery rate increases to 97% in the mid-1980s. Thus, on average, the most recent period is characterized by an almost frictionless financial environment. The reduction in the average level of financial rigidities accounts not only for the decrease in bankruptcy costs linked to the Bankruptcy Reform Act of 1978 (see White, 1983) but also for other changes in the US financial system. The decades under analysis are characterized by the IT revolution, waves of regulation and deregulation, development of new products, and improvements in the assessment of risk. All of these factors define the level of financial rigidity in terms of the model economy. Thus, the improvements in the conditions of access to credit are reflected by the 70% reduction in the size of the financial rigidity operating in the model economy.

Finally, I describe the estimated breaks for the *size of exogenous shocks*. The size of financial shocks has increased over time, which implies a higher exposure to financial risk in the model economy. The size of the wealth shock doubles in the 1970s and it doubles again during the Great Moderation. Larger balance sheet shocks affecting the model economy reflect the increasing sensitivity of the system to asset price movements. Note that the U.S. data have been characterized by several price "bubbles" over the past few decades, such as, the dramatic rise in U.S. stock prices during the late 1990s or the housing bubble during the early 2000s. The size of the shock to the marginal bankruptcy cost more than doubles in the 1970s. But the size of the shock remains stable during the Great Moderation.

The size of the remaining shocks increases in the 1970s and decreases in the mid-1980s. In particular, during the Great Inflation, the size of the investment-specific technology shock increases by 23%; that of the price and wage markup shocks by 75% and 38%, respectively; and the size of the monetary policy shock more than doubles. The size of all nonfinancial shocks decreases during the Great Moderation by a minimum of 20% for the wage markup shock and a maximum of 60% for the monetary policy shock.

4.5 Model evaluation

I study the model fit of the data by performing posterior predictive checks. I focus on analyzing the performance of the model in replicating the observed swings in cyclical volatility. To do so, I generate 1000 samples of 200 observations (after a burn-in period of 1000 observations) from the model economy using every 1000th posterior draw. I filter the data in log-levels obtained from the simulation using the Hodrick-Prescott filter and compute the standard deviation of the cyclical component. Table 5 reports the model-implied ratios of volatilities for the cyclical component. In particular, I report the median and 90% credible intervals, which are due to both parameter and small-sample uncertainty. Given that likelihood-function-based estimation operates by trying to match the entire autocovariance function of the data, there is a tension between matching standard deviations and other second moments of the data. Therefore, the researcher should not expect a perfect accounting of the observed cyclical volatilities. Moreover, in the estimation exercise, I use data in log-levels and first differences instead of cyclical data.

The model successfully generates an enlargement of cyclical volatility for all variables during the Great Inflation. The simulated economy replicates the observed discrepancy in the relative size of the immoderation of nominal variables and credit spreads with respect to the remaining variables. The theoretical framework also delivers the differences in size of the slowdown in the volatility of real variables, nominal outcomes, and the credit spread. However, while the magnitude of the moderation in real variables and inflation is smaller than the observed one, the model-implied reduction for interest rates and credit spreads matches the data.

The posterior predictive check also delivers that the model is successful at generating the divergent pattern in volatility for balance sheet variables. In particular, the model implies a 70% increase in the cyclical volatility of net worth. I also explore the model-implied changes in the cyclical volatility of credit and leverage, which are not included in the information set used to estimate the model. It is noteworthy that the ability of the model to match the size of the immoderation in credit and the discrepancies in the relative size of the volatility increase between credit and net worth. Given that the model is able to replicate to a large extent the stylized facts presented in Tables (1) and (2), I conclude that the model proposed in this paper is a good candidate for analyzing the U.S. business cycle properties for real, nominal, and financial variables.

4.5.1 What does μ_t stand for?

I have introduced time variation in the marginal bankruptcy cost parameter arguing that, in this way, I can attempt to capture variations in the conditions of access to credit at business cycle frequencies. As such, it can be interpreted as a model-based measure of the financial distress present in the economy. In this section, I compare the smoothed series for the marginal bankruptcy cost with empirical measures of financial stress and lending standards. Figure 1 shows the smoothed series for $\ln \mu_t$ against the financial stress index produced by the Kansas City Fed in the upper panel and against the net percentage of domestic banks tightening standards for commercial and industrial loans to large and middle-market firms in the lower panel. These two series are available starting in 1990. The smoothed series for the marginal bankruptcy cost captures well the downward trend in both credit standards (loosening of credit standards) and financial stress present in the U.S. economy until 1995. After 1995, the lending terms get tighter for about 5 years, which coincides with an increase in financial stress as measured by the Kansas City Fed. The model-implied measure of financial rigidities not only presents a positive trend during this period, but also delivers the rapid increase in financial stress and the sudden tightening in lending standards at the end of 1998 and mid to late 2000. The model-implied series also mimics the reduction in financial stress and the corresponding loosening of business lending standards over the 2002–04 period and the slight buildup toward the end of the sample. Therefore, it seems reasonable to attach to μ_t the interpretation of the model variable summarizing the level or strength of financial rigidities in the model economy.

5 Assessing the Drivers of the Great Inflation, the Great Moderation, and the Financial Immoderation

In this section, I analyze the contribution to the model-implied changes in business cycle properties of each of the potential candidates. To do so, I perform two sets of counterfactual exercises. In the first set, I explore the sources of the Great Inflation. I analyze the drivers of the Great Moderation and the immoderation of balance sheet variables in the second set of counterfactual exercises. In the counterfactuals labeled *monetary policy*, I analyze the role played by the estimated changes in the response of the monetary authority to deviations of inflation and output growth from the target. I study the relative importance of changes in the unconditional mean for the marginal bankruptcy cost in the counterfactuals labeled *financial institutions*. I determine the relevance of changes in both financial institutions and the monetary policy stance in the counterfactuals labeled *all institutions* and the relevance of the luck hypothesis in *all shocks*. I establish the relative role played by only financial shocks in the counterfactuals labeled *financial shocks* and by the remaining shocks in the ones labeled *nonfinancial shocks*.

For illustrative purposes, let us consider the *monetary policy* counterfactual for the Great Inflation. I proceed by performing 1000 simulations for each 1000th draw in the posterior simulator using the following procedure:

1. Simulate the model economy for 200 periods (after a burn-in of 1000 observations) using the parameter vector characterizing the 1954–70 sample period. Obtain the cyclical component.

2. Simulate the model economy for 200 periods (after a burn-in of 1000 observations) using the parameter vector characterizing the 1970–84 sample period. Obtain the cyclical component.

3. Compute the ratio of standard deviations of the cyclical components.

4. Simulate the model economy for 200 periods (after a burn-in of 1000 observations) using the parameter vector characterizing the 1954–70 period but with the monetary policy coefficients of the 1970–84 parameter vector. Obtain the cyclical component.

5. Compute the ratio of cyclical standard deviations with respect to those obtained in step 1.

6. Compute the percentage of the ratio obtained in step 3 attributable to the ratio in step 5.

In this way, I single out the role played by the estimated changes in the conduct of monetary policy in accounting for the increase in volatility during the 1970s.

Table 6 reports the percentage of the total increase or decrease in the cyclical standard deviation generated by the model that can be accounted for by the corresponding counterfactual. A dash indicates that the direction of the counterfactual change is at odds with the model-implied changes in volatilities. In the first counterfactual exercise, I analyze the role played by the estimated changes in the response of the monetary authority to deviations of inflation and output growth from the target in the 1970s. The estimated loosening of the response to inflation and the tightening in the response to output account for the following percentages of the model-implied increase in cyclical volatility: 24% for inflation; 12% for the nominal interest rate, wages, and consumption; and 5% on average for net worth, output, and hours.

The counterfactual labeled *financial institutions* shows that the estimated 10% increase in the level of financial rigidity accounts for an average of 3% of the model-implied increase in the volatility of the cyclical component of all variables. Therefore, as compiled in *all institutions*, the relative role played by changes in institutions in the Great Inflation is relegated to accounting for an average of 4% of the model-implied immoderation in output, hours, and net worth. But the institutional changes are able to account for 24% of the model-implied increase in the variability in inflation, about 12% of that in the policy rate and wages, and 14% of the immoderation in consumption. Comparing these results with the following row where I report the percentages of the model-implied increase in cyclical volatilities accounted for by the estimated changes in the size of exogenous shocks, I conclude that while the institutional changes are needed to replicate the model-implied increase in the volatility of inflation, the larger volatility of the remaining variables can only be explained by the estimated change in the size of exogenous shocks.

The conclusion is quite different when analyzing the main sources of the Great Moderation. The counterfactuals *all institutions* and *all shocks* show that the slowdown in cyclical volatility characterizing the post-1984 period cannot be explained by the model without the estimated institutional changes. The combined increase in the size of financial shocks and reduction in the size of the remaining shocks can only account for 53% of the smoothing in consumption and 68% of the reduction in wages, and over-predicts the immoderation in business wealth. The effect on the remaining variables is at odds with the observed evolution of cyclical volatility. The estimated institutional changes, however, account for about 75% of the model-implied moderation in investment and about 60% of the smoothing in output, hours, inflation, and interest rate variability. The new institutional framework overestimates the moderation of credit spreads by about 30%.

Summing up, my model predicts that the Great Inflation was mostly due to bad luck, but the Great Moderation is the result of better institutions in the form of a hawkish monetary policy regime and an easier access to credit for corporations. Although credit markets are almost frictionless in the steady state, the actual conditions of access to external financing still present a significant degree of time variation as shown in figure 1. Moreover, the immoderation in corporate balance sheet variables characterizing the Great Moderation era is driven by the larger exposure to financial risk associated with larger wealth shocks hitting the US economy.

6 Economic Implications

The economic implications of standard real and nominal shocks in a financial accelerator model have been analyzed in the literature. The distinctive feature of this paper is the presence of financial shocks. Therefore, in this section, I focus on the study of the relative importance and propagation dynamics of financial shocks.

6.1 Variance decomposition and historical decomposition

Table 7 provides the median variance decomposition at business cycle frequencies. I compute the spectral density of the observable variables implied by the DSGE model evaluated at each $1000th$ posterior draw and use an inverse difference filter to obtain the spectrum for the level of output, investment, consumption, wages, and net worth. I define business cycle fluctuations as those corresponding to cycles between 6 and 32 quarters and consider 500 bins for frequencies covering these periodicities.

The results state that financial shocks are an important source of business cycle fluctuations. Financial shocks are the main source of the variance in investment, the policy rate, the credit spread, and business net worth. Financial shocks also play a non-negligible secondary role as drivers of the remaining variables. While the relative role played by the shock to the marginal bankruptcy cost is about 80% smaller than the one played by the wealth shock for most variables, the shock driving time-variation in the level of financial rigidities is a key driver of the credit spread, accounting for almost half of its variation. Levin, Natalucci, and Zakrajšek (2004) estimate a partial equilibrium version of the BGG model using micro data and conclude that exogenous disturbances in the marginal bankruptcy cost are the main driver of the external finance premium. Thus, they provide micro evidence supporting the result presented in this paper using aggregate data: In order to deliver empirically plausible swings in the cost of external financing in a model with the financial accelerator, time variation in the level of financial rigidity should be incorporated.

The contribution of financial shocks to the variance of investment at business cycle frequencies ranges between 35% in the 1950s and 1960s and almost 50% during the Great Inflation. In the most recent period, these shocks explain up to 40% of the variation in investment. Their relative role in driving fluctuations in output is smaller, accounting for 16% of its variance during the Great Moderation. However, in the 1970s, financial shocks are the most important driver of output fluctuations: Their contribution is 32%, which exceeds the contribution of technology shocks. It is also during the Great Inflation when financial shocks are the main driver of hours worked and inflation accounting for 36% and 42% of the variance, respectively. Financial shocks account for 60% of the variation in nominal interest rates during the Great Inflation and for 30% to 40% in the other subperiods.

Given the estimated changes in the relative contribution of financial shocks to the variance of nonfinancial variables, I argue that the role played by financial shocks as drivers of business cycle fluctuations is sensitive to the institutional framework characterizing the U.S. economy. To explore this hypothesis, I calculate the variance decomposition in counterfactuals scenarios (see table 8). The conditions of access to credit, summarized by the marginal bankruptcy cost at the steady state, are key in determining the role played by financial shocks as drivers of business cycle fluctuations for all nonfinancial variables under analysis. While the estimated 10% tightening of the conditions of access to credit during the Great Inflation has a negligible effect in the relative contribution of both financial shocks to the variance of the variables under analysis, the estimated 70% reduction during the Great Moderation has a large impact. If the innovations in the financial sector and regulatory changes had not taken place so that the conditions of access to credit since the mid-1980s were identical to the ones in the 1970s, financial shocks would have been the main source of variability in the U.S. economy. For example, financial shocks would have accounted for 66% of the variance of output instead of the estimated 16% or 88% of the variability in investment rather than the 40% implied by our estimates. Moreover, these shocks would have explained 90% of the variation in the policy rate and 48% in the variance of inflation instead of 39% and 6%, respectively. I conclude that the institutional changes regarding the functioning of credit markets in the United States helped reduce the vulnerability of the U.S. economy on financial disturbances.

Regarding the influence of the conduct of monetary policy on the role played by financial shocks in driving business cycle fluctuations, table 8 show that, during the Great Inflation, if the monetary authority had reacted to inflation as it did during the 1950s and 1960s, the relative role played by financial shocks in driving inflation and the federal funds rate would have been about 15% smaller. Similarly, if the dovish monetary policy regime in place during the 1970s had been in place during the Great Moderation, financial shocks would have accounted for 50% of the variance in inflation and 70% of the variance in the interest rate.

Therefore, I conclude that the monetary authority successfully minimized the dependence of its target variable—the inflation rate—on credit market disruptions by implementing a hawkish regime during the Great Moderation.

To gain additional insight into the relative role played by financial shocks, I report in figure 2 a time series decomposition of the contribution of financial shocks to the cyclical variance by plotting the cyclical component when all the smoothed shocks are fed to the model (solid line) and when the model is fed only with the estimated smoothed sequence of financial shocks (dashed line). The most remarkable feature of the figure is the comovement between the two lines for output and investment, mostly since the 1970s. While financial shocks play a predominant role pushing investment upward at expansions, they are key in the troughs for output. For example, financial shocks account for a large fraction of the twin recessions of 1980 and 1981–82, refuting the hypothesis that monetary facts were the drivers of these recessions. Financial shocks overheated the economy during the peak preceding the 2007–09 recession.

Finally, I analyze the role played by the investment-specific technology shock in driving business cycle fluctuations.Once financial frictions and financial shocks are in play, the role for the investment-specific technology shock is relatively small. Justiniano, Primiceri and Tambalotti (2011) consider two types of investment shocks: investment-specific technology shocks affecting the transformation of consumption into investment goods and shocks to the marginal efficiency of investment, which ultimately affect the transformation of investment goods into productive capital. They conclude that the relative importance of the former is negligible, but the latter is the main driver of the real business cycle. They state that shocks to the marginal efficiency of investment are a proxy for disturbances to the financial system. My results confirm their conclusions, since financial shocks play a significant role as drivers of real and nominal cycle.

6.2 Impulse response functions

I report the responses to financial shocks in the first 40 quarters in terms of percentage deviations with respect to the steady state. Each plot contains three impulse response functions (IRFs). The dotted line is the IRF computed using the parameter vector characterizing the 1954:Q4–1970:Q1 sample period. The dashed line is the IRF for the 1970s and early 1980s. The solid line is the IRF for the post-1984 period.

6.2.1 Wealth shock

Figure 3 reports the impulse response functions following a wealth shock that, upon impact, induces an increase in entrepreneurial net worth equal to a 1% deviation from its steady-state value in the pre–Great Inflation era. The size of the shock generating such a response upon impact is 0.49. I use the same shock across subsamples to facilitate the comparison. The main messages from the figure are *(i)* the responses upon impact are a positive function of the size of the financial rigidity, and *(ii)* the persistence of the responses is a negative function of the unconditional average of the marginal bankruptcy cost.

Let us first analyze the impulse response functions for net worth. The response upon impact of net worth is 8% larger during the Great Inflation and 47% smaller during the Great Moderation. The IRFs associated with lower unconditional averages for the marginal bankruptcy cost cross the ones for higher levels of financial rigidity from below within the first 14 quarters to lie above them thereafter. This can be easily reconciled from the definition of aggregate net worth. Lower average agency costs alleviate the deadweight loss associated with bankruptcy, $\mu_t G(\bar{\omega}_t) P_{t-1} R_t^k Q_{t-1} K_t$, which implies that for the same initial increase in wealth, the effects are more long-lasting, as more resources are accumulated from period to period. The persistent expansionary effects in business wealth of a positive wealth shock are also linked to the deleveraging process induced by these types of shocks. As reported in figure 5, entrepreneurs proceed to readjust their funding portfolio by reducing their dependence on external financing. The contraction in credit reduces even further the deadweight loss associated with bankruptcy in addition to reducing the principal and interest to pay back to lenders. Moreover, the size of the balance sheet adjustment is a negative function of the size of the financial accelerator. Thus, in an environment with low financial rigidities, as the one characterizing the U.S. during the Great Moderation, a deleveraging of the business sector can be induced by taxing households and transferring the proceeds to entrepreneurs.

A positive wealth shock that increases the value of collateral reduces the probability of default so that financial intermediaries are willing to lend at a lower premium. This movement translates into a negative response upon impact for the external finance premium. As entrepreneurs engage in a deleveraging process, financial intermediaries reduce the price of credit even further in subsequent periods. The response of the external finance premium bottoms out about 3 to 9 basis points below the steady-state level and stays below the steady-state level for over 100 quarters. The lower price of credit and the availability of additional resources caused by the boost in business wealth translate into persistent favorable economic effects. The expansionary effects in real economic variables of a wealth shock translate into an inflationary episode that triggers a tightening of monetary policy.

As is standard in models with the financial accelerator à la BGG, the initial responses of consumption and investment are negatively correlated. The negative response of consumption upon impact is linked to the general equilibrium effects of the model. A nonfundamental increase in entrepreneurial wealth shifts resources from households to the entrepreneurial sector. The reduction in disposable income is not large enough to generate a decrease in consumption of the same magnitude as the increase in entrepreneurial wealth due to the fact that other sources of household wealth, such as labor income, react positively to wealth shocks. In this model, credit supply is funded by deposits so that a reduction in business leverage requires a smaller percentage of household income captured through deposits. Thus, the deleveraging process in the business sector frees up resources for consumption in the household sector, which explains the rebound in consumption about 5 quarters after the shock. The sluggish response of consumption is due to the relatively high degree of habit formation.

6.2.2 Shock to the marginal bankruptcy cost

Figure 4 reports the impulse response functions to marginal bankruptcy shocks. Because negative shocks to agency costs reduce the deadweight loss associated with bankruptcy, the response upon impact to a shock reducing the agency problem is positive for business wealth. I focus on a negative shock to bankruptcy costs, generating upon impact an increase in net worth of 1% in the pre–Great Inflation period. The size of such a shock is 29, which is 60 times larger than the wealth shock necessary to generate a 1% increase in net worth. Put differently, a wealth shock increasing net worth by 1% implies a reduction upon impact in the spread of 3 basis points, while a shock to agency costs that increases net worth 1% upon impact generates an 18 basis point decline in credit spreads. Thus calibrated, the relative magnitude of the peak response to these two expansionary financial shocks is similar for all nonfinancial variables in the system. The timing of the peaks is slightly different depending on the nature of the financial shocks. While all nonfinancial variables except consumption and inflation peak 4 quarters after an expansionary shock to marginal bankruptcy costs, the peak response to a wealth shock is 6 to 7 quarters after the shock. The persistence of the propagation dynamics of a shock to the marginal bankruptcy cost is also significantly smaller than the persistence of the responses to a wealth shock. The expansionary effects of shock that reduces agency costs die out about 5 years after the shock, while the favorable effects of a wealth shock have an "almost permanent" flavor.

An expansionary shock to agency costs creates an incentive for entrepreneurs to select contractual terms with a larger debt-to-net-worth ratio, as the deadweight loss linked to bankruptcy is smaller. There are two opposing effects operating as a result of higher debt-to-net-worth ratios. On the one hand, both the default probability and the default productivity threshold increase, offsetting the effect of lower bankruptcy costs in the event of default. I label this effect the *default effect*. On the other hand, there is a *mass effect*: There is an increase in capital investment given that a larger set of resources is available. Larger amounts of capital holdings imply a larger equity value through an increase in total capital returns. The impulse response for net worth shows that while the mass effect dominates at first, the default effect becomes the driving force after 10 quarters. The response of investment upon impact is larger than the response I obtained to a wealth shock due to the *mass effect* explained above. Irrespective of the relative dominance of this effect in terms of shaping the response of entrepreneurial wealth, the increase in the pool of resources available for purchasing capital enhances investment activity in the economy.

As stated earlier, the significant decline in the size of the financial accelerator translates into smaller responses upon impact and larger persistence of the responses in the Great Moderation era.

7 Conclusions

I have estimated a fairly large DSGE model to reexamine the sources of the observed breaks in macroeconomic fluctuations in the U.S. economy. The estimation indicates that while the Great Inflation was mostly due to bad luck, the Great Moderation is the result of changes in the institutional framework. Both improvements in the financial system and changes in the conduct of monetary policy are key for explaining the slowdown in fluctuations at business cycle frequencies since the mid-1980s. The easier access to credit has been paired with higher exposure to financial risk in the form of larger financial shocks hitting the U.S. economy, which is key in accounting for the immoderation observed in financial variables.

The exploration of the drivers of the U.S. business cycle delivers the finding that financial shocks play a significant role. In particular, they are the main driver of the variances in financial variables, investment, and the nominal interest rate. Financial shocks play an important secondary role as drivers of fluctuations at business cycle frequencies for output, consumption, hours, and inflation. The size of financial shocks has increased over time, while their relative contribution to the variance of nonfinancial variables has not increased dramatically. This outcome is due to the improvements in the institutional framework characterizing the U.S. economy. Thus, I conclude that the hawkish monetary policy regime and the innovations in the financial intermediation process in the mid-1980s have been a safeguard for the vulnerability of the U.S. economy to financial market disruptions. Moreover, the model suggests a policy intervention to reactivate the economy in the midst of a recession paired with high leverage ratios: a "bailout" of the business sector financed by higher household taxes.

Finally, despite concluding that the relative role played by shocks to marginal bankruptcy costs is along the lines of the contribution of monetary policy shocks, the incorporation of time variation in the parameter that controls the level of financial rigidities is key to *(i)* deliver empirically plausible swings in credit spreads in a model with the financial accelerator, and *(ii)* obtain a model based measure of financial stress that closely mimics the dynamics of empirical proxies of financial stress and lending standards. The latter is relevant to assess the health of the U.S. financial system during periods for which none of the empirical measures are available.

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A Tables and Figures

Table 1: Econometric tests: cyclical volatility

	BAI-PERRON		CHOW	Volatility ratio	
				$\frac{1970-1984}{1954-1970}$	$\frac{1984-2006}{1970-1984}$
Output	1984:Q2		34.60***	1.58	0.42
Investment	1984:Q1		36.24***	1.53	0.43
Consumption	1984:Q2		19.54***	1.74	0.44
Inflation	1970:Q1	1981:Q2	42.95**	2.56	0.36
Federal funds rate	1972:Q4	1983:Q1	44.66***	2.64	0.50

Notes: The data range from 1954:Q4 to 2006:Q4 for all variables. The cyclical component is extracted using the Hodrick-Prescott filter for the quarterly frequency ($\lambda = 1600$). The log-likelihood ratio statistic is distributed as χ^2 with $(m-1)k$ degrees of freedom, where m is the number of subsamples. The critical values when there are two breaks are 4.61 at 10%, 5.99 at 5%, and 9.21 at 1%. If the statistic is above the critical value, the null hypothesis of no structural change can be rejected. The symbol * indicates we can reject the null of parameter constancy at 10%, ** at 5%, and *** at 1%.

Table 2: Econometric tests: cyclical volatility

	CHOW	Volatility ratio	
		$\frac{1970-1984}{1954-1970}$	$\frac{1984-2006}{1970-1984}$
Corporate net worth 1	29.17***	1.67	1.74
Corporate net worth 2	38.15***	1.14	1.98
Leverage 1	23.93***	3.36	1.11
Leverage 2	46.83**	3.44	1.66
Tobin's q	0.76	1.26	1.16
Equity q	6.04**	1.30	1.48
Net increase in credit market liabilities	30.64***	2.12	1.16
Net increase in corporate bonds	44.18***	1.69	2.76
Equity payout	42.51***	2.07	1.83
Spread: Baa-Aaa	31.98***	3.00	0.33
Spread: Aaa-ffr	36.78***	2.59	0.49
Spread: Baa-ffr	39.69***	2.65	0.47
Spread: Prime-ffr	65.73***	1.52	0.23
Spread: Aaa-10y	15.68***	1.75	0.86
Spread: Baa-10y	35.22***	2.33	0.50

Notes: The data range from 1954:Q4 to 2006:Q4 for all variables. Net worth 1 is defined as total assets minus total liabilities in the nonfinancial corporate business sector and net worth 2 is defined as tangible assets minus credit market liabilities. Leverage 1 refers to the credit market liabilities-to-net-worth 1 ratio and leverage 2 to the credit market liabilities-to-net-worth 2 ratio. Tobin's q is the ratio of the sum of equities and liabilities to total assets and equity q is defined as the market value of equities to net worth (measure 1) ratio. The cyclical component is extracted using the Hodrick-Prescott filter for the quarterly frequency ($\lambda = 1600$). The log-likelihood ratio statistic is distributed as χ^2 with $(m-1)k$ degrees of freedom, where m is the number of subsamples. The critical values when there are two breaks are 4.61 at 10%, 5.99 at 5%, and 9.21 at 1%. If the statistic is above the critical value, the null hypothesis of no structural change can be rejected. The symbol * indicates we can reject the null of parameter constancy at 10%, ** at 5%, and *** at 1%.

Table 3: Parameters estimated using the full sample

	Prior			Posterior	
	Density	**Para 1**	**Para 2**	**Median**	**95% CI**
δ	Fixed	0.03	–	–	–
$(G/Y)^{\star}$	Fixed	0.22	–	–	–
$100[F(\bar{\omega})]^{\star}$	Fixed	0.75	–	–	–
λ_p	Fixed	0.20	–	–	–
λ_w	Fixed	0.20	–	–	–
$100\ln(H^{\star})$	Fixed	0.54	–	–	–
$100\Upsilon_z$	Fixed	0.45	–	–	–
$100\,[1/\beta-1]$	Beta	0.25	0.10	0.21	[0.12, 0.31]
$100\,[1/\gamma-1]$	Gamma	1.48	0.50	2.01	[1.02, 3.12]
σ_{ω}^2	$\mathcal{IG}$	0.16	4.00	0.30	[0.22, 0.41]
$\pi_n^{\star}$	$\mathcal{N}$	3.00	1.00	2.48	[2.08, 2.92]
$400\left[\left(R_{\star}^k/R_{\star}\right)-1\right]$	Gamma	1.75	0.25	1.50	[1.13, 1.88]
$\phi=\Phi/y_{\star}$	Beta	0.35	0.15	0.52	[0.40, 0.65]
ι_p	Beta	0.50	0.15	0.11	[0.03, 0.20]
ι_w	Beta	0.50	0.15	0.06	[0.02, 0.11]
ξ_p	Beta	0.66	0.15	0.79	[0.73, 0.83]
ξ_w	Beta	0.66	0.15	0.59	[0.49, 0.69]
θ_p	Beta	0.50	0.20	0.67	[0.54, 0.79]
θ_w	Beta	0.50	0.20	0.70	[0.45, 0.88]
α	Beta	0.30	0.03	0.16	[0.15, 0.18]
ξ	$\mathcal{N}$	4.00	1.00	0.61	[0.43, 0.83]
a”	Gamma	1.00	0.50	0.94	[0.25, 1.78]
ν	Gamma	2.00	0.75	0.97	[0.53, 1.46]
h	Beta	0.60	0.20	0.85	[0.79, 0.90]
ρ_r	Beta	0.50	0.10	0.76	[0.72, 0.80]
ρ_z	Beta	0.40	0.10	0.43	[0.31, 0.54]
ρ_{ζ}	Beta	0.60	0.20	0.91	[0.86, 0.95]
ρ_{φ}	Beta	0.60	0.20	0.96	[0.94, 0.97]
ρ_x	Beta	0.60	0.20	0.91	[0.83, 0.96]
ρ_{λ_p}	Beta	0.60	0.20	0.98	[0.95, 0.99]
ρ_{λ_w}	Beta	0.60	0.20	0.98	[0.97, 0.99]
ρ_b	Beta	0.60	0.20	0.46	[0.29, 0.65]
ρ_g	Beta	0.60	0.20	0.99	[0.98, 0.99]
ρ_{mp}	Beta	0.60	0.20	0.13	[0.05, 0.22]

Notes: Para 1 and Para 2 list the means and the standard deviations for Beta, Gamma, and Normal distributions; the upper and lower bound of the support for the uniform distribution; s and ν for the inverse Gamma distribution, where $p_{IG}(\sigma|\nu,s) \propto \sigma^{-\nu-1}e^{-nus^2/2\sigma^2}$. The effective prior is truncated at the boundary of the determinacy region.

Table 4: Parameters subject to structural breaks

	Prior			Posterior	
	Density	**Para 1**	**Para 2**	**Median**	**95% CI**
ψ_{π_1}	$\mathcal{N}$	1.50	0.50	1.46	[1.26, 1.68]
ψ_{π_2}	$\mathcal{N}$	1.50	0.50	1.26	[1.14, 1.40]
ψ_{π_3}	$\mathcal{N}$	1.50	0.50	2.09	[1.72, 2.47]
ψ_{y_1}	$\mathcal{N}$	0.50	0.30	0.19	[0.12, 0.27]
ψ_{y_2}	$\mathcal{N}$	0.50	0.30	0.27	[0.12, 0.43]
ψ_{y_3}	$\mathcal{N}$	0.50	0.30	0.49	[0.35, 0.63]
$\mu_1^\star$	Beta	0.30	0.05	0.10	[0.07, 0.15]
$\mu_2^\star$	Beta	0.30	0.05	0.11	[0.07, 0.15]
$\mu_3^\star$	Beta	0.30	0.05	0.03	[0.02, 0.04]
σ_{φ_1}	$\mathcal{IG}$	0.001	4.00	0.09	[0.07, 0.11]
σ_{φ_2}	$\mathcal{IG}$	0.001	4.00	0.22	[0.18, 0.28]
σ_{φ_3}	$\mathcal{IG}$	0.001	4.00	0.23	[0.16, 0.30]
$100(\sigma_{x_1})$	$\mathcal{IG}$	0.10	4.00	0.43	[0.31, 0.58]
$100(\sigma_{x_2})$	$\mathcal{IG}$	0.10	4.00	0.89	[0.62, 1.22]
$100(\sigma_{x_3})$	$\mathcal{IG}$	0.10	4.00	2.11	[1.64, 2.59]
$100(\sigma_{z_1})$	$\mathcal{IG}$	0.10	4.00	1.40	[1.16, 1.67]
$100(\sigma_{z_2})$	$\mathcal{IG}$	0.10	4.00	1.35	[1.12, 1.62]
$100(\sigma_{z_3})$	$\mathcal{IG}$	0.10	4.00	1.01	[0.86, 1.16]
$100(\sigma_{\zeta_1})$	$\mathcal{IG}$	0.10	4.00	1.26	[0.94, 1.63]
$100(\sigma_{\zeta_2})$	$\mathcal{IG}$	0.10	4.00	1.55	[1.21, 1.96]
$100(\sigma_{\zeta_3})$	$\mathcal{IG}$	0.10	4.00	1.02	[0.80, 1.26]
$100(\sigma_{\lambda_1^p})$	$\mathcal{IG}$	0.10	4.00	0.16	[0.12, 0.20]
$100(\sigma_{\lambda_2^p})$	$\mathcal{IG}$	0.10	4.00	0.28	[0.22, 0.34]
$100(\sigma_{\lambda_3^p})$	$\mathcal{IG}$	0.10	4.00	0.17	[0.14, 0.21]
$100(\sigma_{\lambda_1^w})$	$\mathcal{IG}$	0.10	4.00	0.21	[0.17, 0.27]
$100(\sigma_{\lambda_2^w})$	$\mathcal{IG}$	0.10	4.00	0.29	[0.22, 0.36]
$100(\sigma_{\lambda_3^w})$	$\mathcal{IG}$	0.10	4.00	0.24	[0.20, 0.29]
$100(\sigma_{b_1})$	$\mathcal{IG}$	0.10	4.00	3.68	[2.36, 5.19]
$100(\sigma_{b_2})$	$\mathcal{IG}$	0.10	4.00	3.88	[2.60, 5.27]
$100(\sigma_{b_3})$	$\mathcal{IG}$	0.10	4.00	3.02	[1.96, 4.28]
$100(\sigma_{r_1})$	$\mathcal{IG}$	0.10	4.00	0.13	[0.11, 0.16]
$100(\sigma_{r_2})$	$\mathcal{IG}$	0.10	4.00	0.37	[0.31, 0.45]
$100(\sigma_{r_3})$	$\mathcal{IG}$	0.10	4.00	0.15	[0.13, 0.19]
$100(\sigma_{g_1})$	$\mathcal{IG}$	0.10	4.00	0.35	[0.29, 0.41]
$100(\sigma_{g_2})$	$\mathcal{IG}$	0.10	4.00	0.42	[0.35, 0.49]
$100(\sigma_{g_3})$	$\mathcal{IG}$	0.10	4.00	0.29	[0.24, 0.33]

Notes: Para 1 and Para 1 list s and ν for the inverse Gamma distribution, where $p_{IG}(\sigma|\nu, s) \propto \sigma^{-\nu-1}e^{-nus^2/2\sigma^2}$. The effective prior is truncated at the boundary of the determinacy region.

Table 5: Model fit: Ratio of standard deviations, cyclical component

Series	$\frac{1970-1984}{1954-1970}$			$\frac{1984-2006}{1970-1984}$		
	Data	Model		Data	Model	
		Median	90%		Median	90%
Output	1.58	1.72	[1.48, 1.97]	0.42	0.58	[0.50, 0.68]
Investment	1.53	1.75	[1.45, 2.02]	0.43	0.58	[0.49, 0.70]
Consumption	1.74	1.13	[1.02, 1.31]	0.44	0.81	[0.71, 0.93]
Wage	1.63	1.38	[1.16, 1.60]	0.51	0.70	[0.59, 0.79]
Hours	1.47	1.71	[1.48, 1.94]	0.64	0.58	[0.50, 0.68]
Inflation	2.56	1.89	[1.56, 2.21]	0.36	0.50	[0.41, 0.58]
Nominal interest rate	2.64	2.16	[1.81, 2.53]	0.50	0.51	[0.43, 0.60]
Net worth	1.14	1.58	[1.34, 1.89]	1.98	1.71	[1.28, 2.13]
Spread	2.33	2.23	[1.79, 2.75]	0.50	0.52	[0.42, 0.69]
Leverage	3.44	1.93	[1.37, 2.49]	1.66	2.65	[1.81, 3.60]
Debt	1.69	1.88	[1.36, 2.41]	2.76	2.71	[1.85, 3.67]

Notes: For each 1000th parameter draw, I generate 1000 samples with the same length as the data after discarding 1000 initial observations. I HP filter the nonstationary data generated by the model.

Table 6: Counterfactuals: Percentage of the model-implied change in cyclical standard deviations

GREAT INFLATION

	Y	**I**	**C**	**H**	**W**	π	R	**N**	$\frac{\mathbb{E}\left(R^k_{t+1}\right)}{R_t}$
Monetary policy	4	–	15	5	12	24	12	6	1
Financial institutions	2	3	7	2	2	1	2	2	3
All institutions	**4**	–	**14**	**4**	**12**	**24**	**12**	**5**	**2**
All shocks	**96**	**100**	**99**	**96**	**91**	**66**	**86**	**96**	**99**
Financial shocks	47	64	28	47	8	33	49	81	97
Nonfinancial shocks	63	49	79	62	85	42	50	23	7

GREAT MODERATION

	Y	**I**	**C**	**H**	**W**	π	R	**N**	$\frac{\mathbb{E}\left(R^k_{t+1}\right)}{R_t}$
Monetary policy	52	48	–	5	5	51	31	–	–
Financial institutions	15	28	2	14	–	36	49	–	132
All institutions	**62**	**75**	**3**	**62**	**8**	**57**	**60**	–	**132**
All shocks	–	–	**53**	–	**68**	–	–	**128**	–
Financial shocks	–	–	–	–	–	–	–	37	–
Nonfinancial shocks	46	35	117	46	99	38	34	–	1

Notes: I include a dash (-) when the direction of the counterfactual-implied change is at odds with the model-implied changes in volatilities. Y stands for real output, I for real investment, C for real consumption, H for hours, W for real wages, π for inflation, R for the policy interest rate, N for real net worth, $\mathbb{E}\left(R^k_{t+1}\right)/R_t$ for the external finance premium or credit spread, B for real debt, and B/N for leverage.

Table 7: Variance decomposition at business cycle frequencies: Medians

	Bankr. cost	Wealth	Neutral	I-shock	P-Markup	W-markup	Inter	MP	Gov
Output									
Pre-1970	2	10	48	10	12	12	2	3	1
1970-1984	7	24	19	8	15	9	2	15	1
Post-1984	2	14	33	6	18	22	1	4	1
Investment									
Pre-1970	4	21	34	16	14	6	1	5	0
1970-1984	10	38	10	10	13	3	0	16	0
Post-1984	4	36	18	9	17	9	2	4	0
Consumption									
Pre-1970	0	1	46	0	3	20	28	0	0
1970-1984	0	4	34	0	7	26	26	2	0
Post-1984	1	15	28	1	3	27	26	0	0
Hours									
Pre-1970	3	17	12	16	19	21	4	6	2
1970-1984	8	28	5	9	18	11	2	18	1
Post-1984	3	19	10	8	24	30	1	5	1
Wage									
Pre-1970	1	6	46	8	24	7	4	3	1
1970-1984	5	16	19	6	31	6	3	15	1
Post-1984	1	6	34	4	37	12	2	4	0
Inflation									
Pre-1970	2	20	28	8	15	13	9	4	0
1970-1984	5	37	11	4	16	13	4	11	0
Post-1984	2	4	33	5	26	21	4	5	0
Nominal rate									
Pre-1970	5	39	5	19	4	4	12	13	1
1970-1984	8	52	1	9	2	3	4	20	1
Post-1984	9	30	6	23	9	4	8	11	1
Net Worth									
Pre-1970	2	61	2	28	2	0	0	5	0
1970-1984	3	72	1	12	1	1	0	10	0
Post-1984	0	97	0	2	0	0	0	0	0
Spread									
Pre-1970	39	44	6	6	2	1	1	1	0
1970-1984	52	41	1	2	1	0	0	2	0
Post-1984	41	59	0	0	0	0	0	0	0

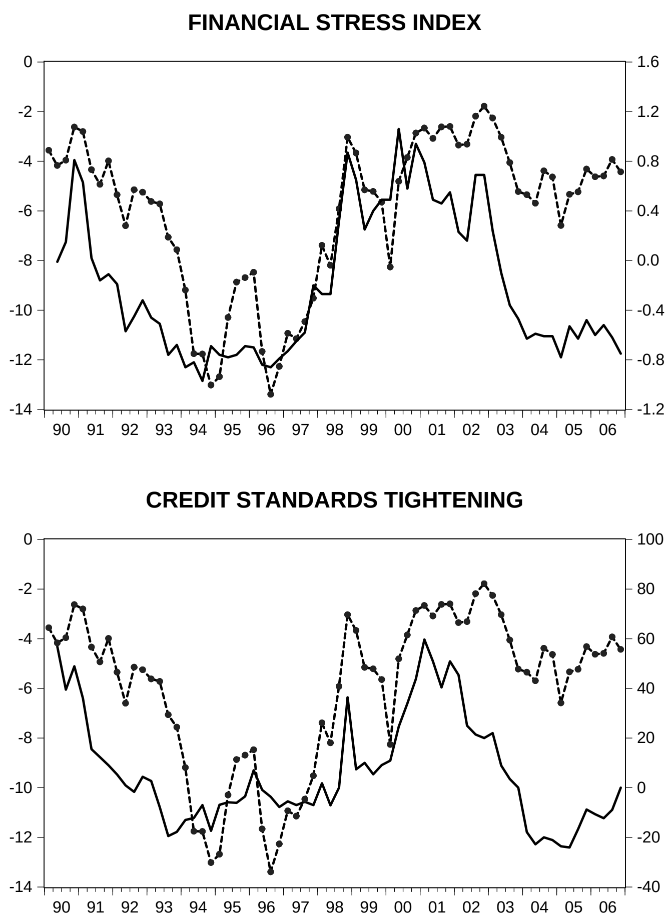
Notes: I use periodic components of cycles between 6 and 32 quarters. I compute the variance decomposition at the posterior median using the spectrum of the model. For output, investment, consumption, wages, and net worth, I use an inverse difference filter in order to report the decomposition for levels. I consider 500 bins for frequencies covering the periodicities of interest.

Table 8: Counterfactual variance decomposition: contribution of financial shocks

GREAT INFLATION										
		Y	**I**	**C**	**H**	**W**	π	R^n	**N**	**Spread**
Financial institutions										
Bankruptcy cost	Actual	7	10	0	8	5	5	8	3	52
	Counter	7	10	0	8	5	5	8	3	53
Wealth	Actual	24	38	4	28	16	37	52	72	41
	Counter	24	38	4	28	16	36	52	72	41
Monetary Policy										
Bankruptcy cost	Actual	7	10	0	8	5	5	8	3	52
	Counter	6	9	0	7	4	5	8	3	52
Wealth	Actual	24	38	4	28	16	37	52	72	41
	Counter	20	34	5	25	13	34	45	71	41

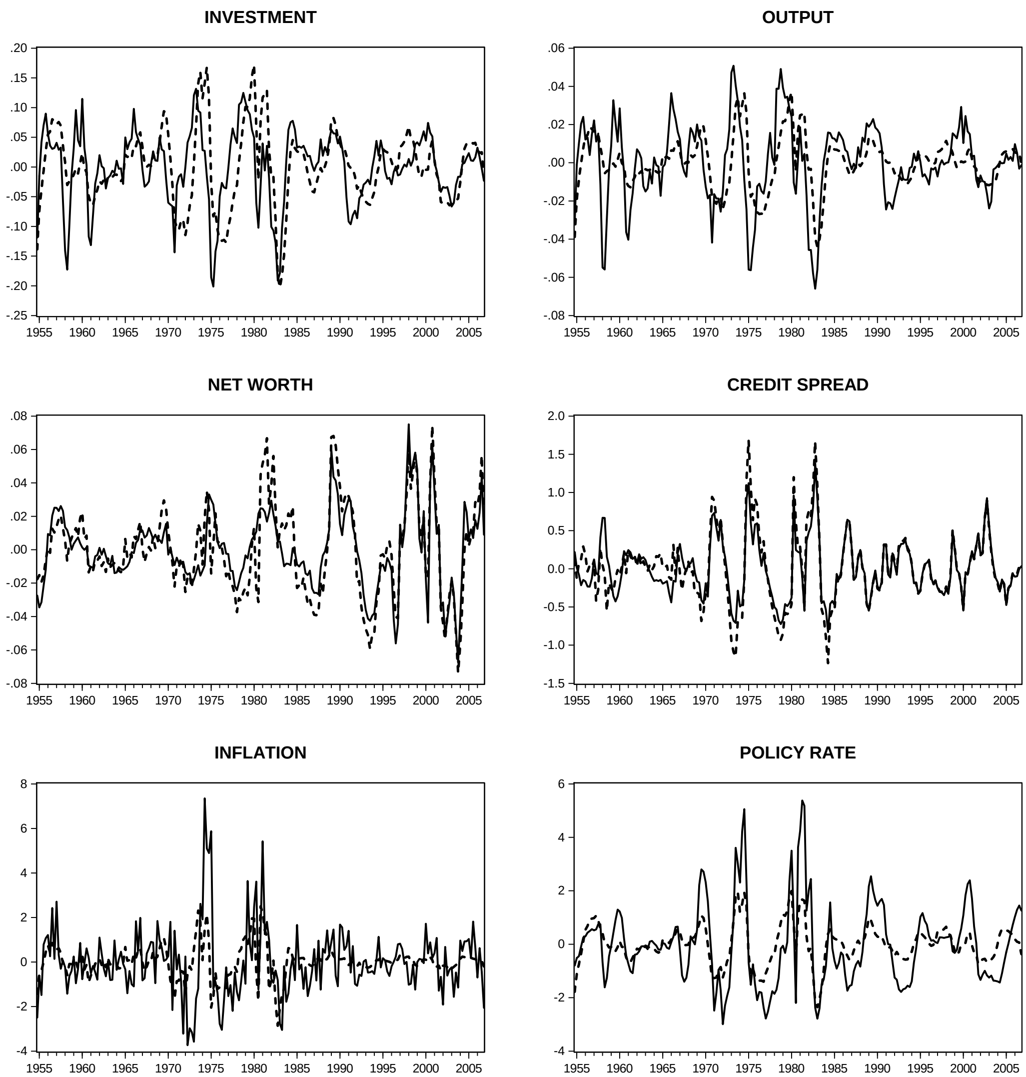
GREAT MODERATION										
		Y	**I**	**C**	**H**	**W**	π	R^n	**N**	**Spread**
Financial institutions										
Bankruptcy cost	Actual	2	4	1	3	1	2	9	0	41
	Counter	4	4	1	4	3	4	6	0	18
Wealth	Actual	14	36	15	19	6	4	30	97	59
	Counter	62	84	51	70	42	44	84	97	81
Monetary Policy										
Bankruptcy cost	Actual	2	4	1	3	1	2	9	0	41
	Counter	4	6	0	5	3	4	7	0	42
Wealth	Actual	14	36	15	19	6	4	30	97	59
	Counter	23	40	8	29	15	46	62	98	58

Figure 1: Time-variation in marginal bankruptcy cost



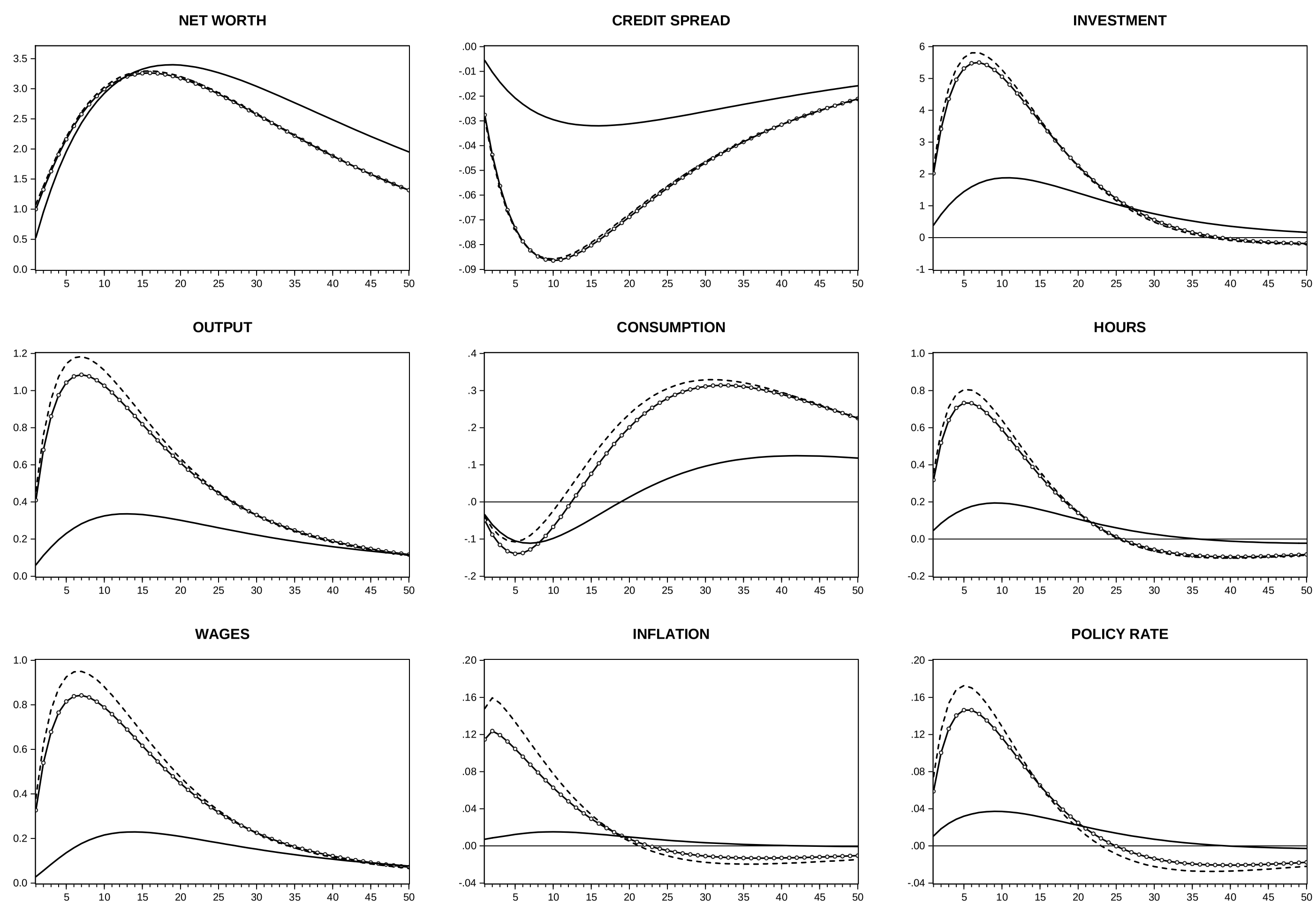
Notes: The dotted dashed line represents the log of the smoothed marginal bankruptcy cost and it is measured in the left vertical axis. The solid line, which is measured in the right vertical axis, represents the financial stress index produced by the Kansas City Fed in the upper panel and the net percentage of domestic banks tightening standards for commercial and industrial loans to large and middle-market firms in the lower panel.

Figure 2: Smoothed cyclical component



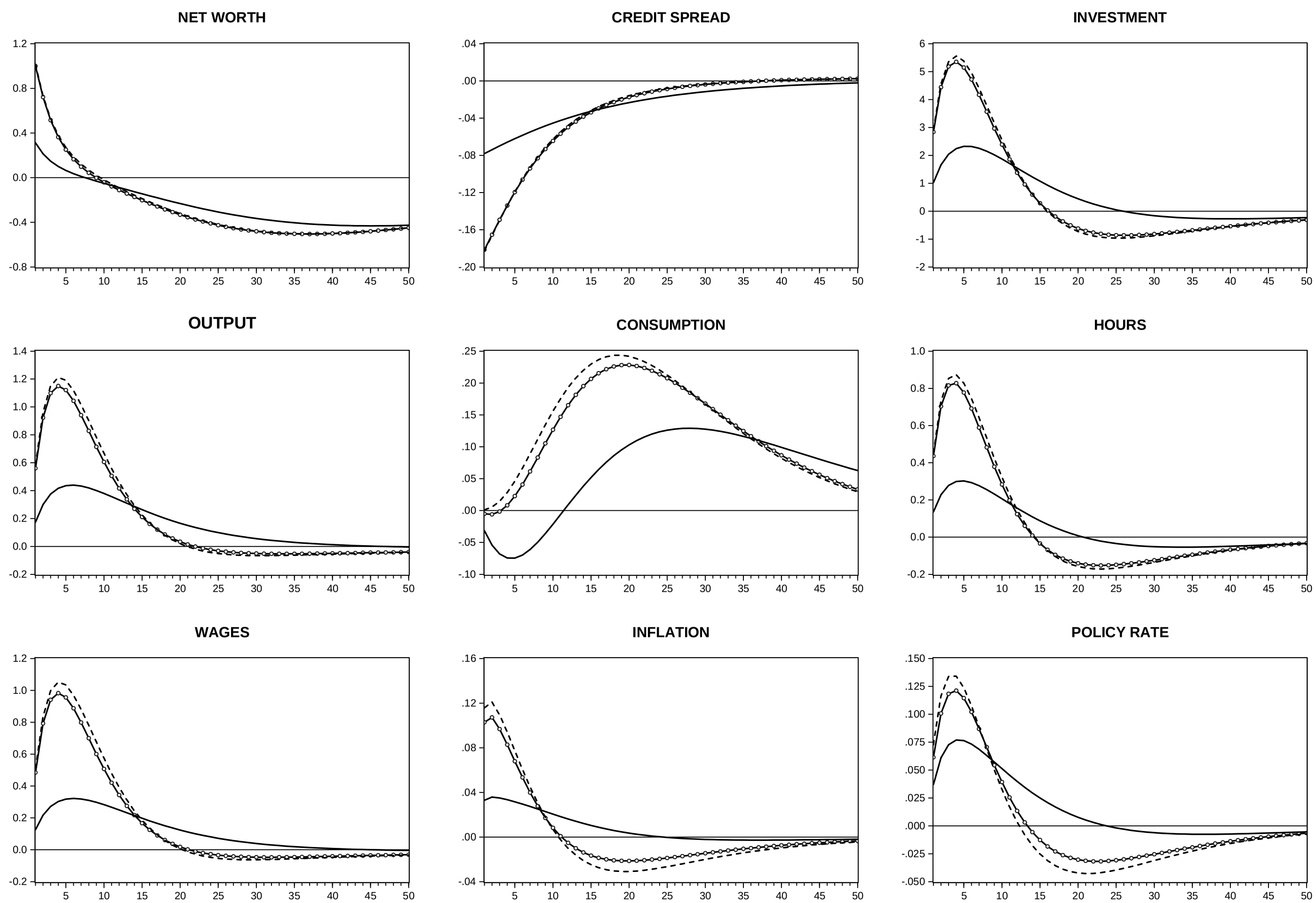
Notes: The solid line is the cyclical component of the variable when the smoothed shocks are fed to the model. The dashed line is the cyclical component when only the smoothed financial shocks are fed to the model.

Figure 3: Impulse response functions with respect to a wealth shock



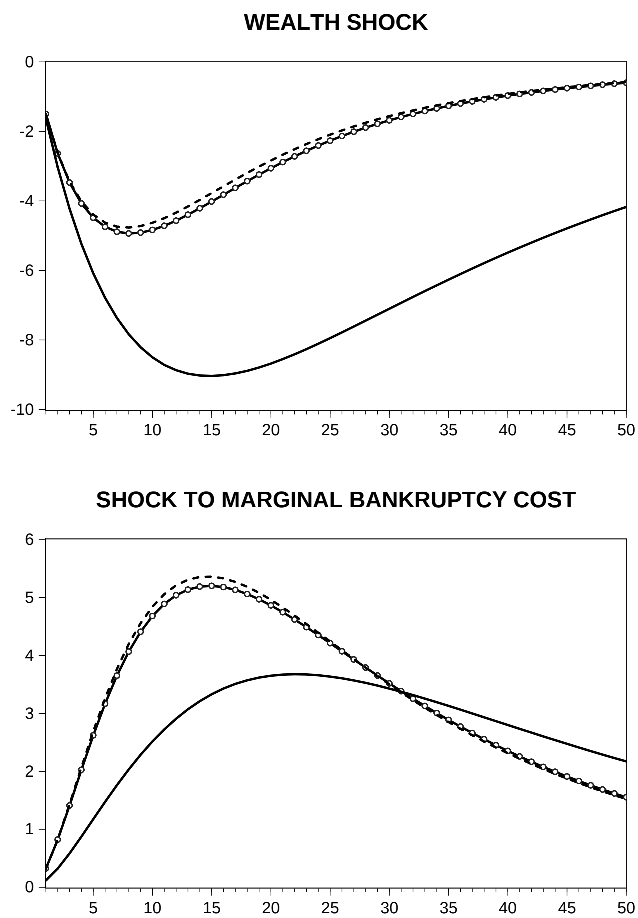
Notes: The dotted line is the IRF for the 1954:Q4–1970:Q1 period, the dashed line is the IRF for 1970:Q2–1984:Q2, and the solid line is the IRF for the post-1984:Q2 period.

Figure 4: Impulse response functions with respect to a shock to the marginal bankruptcy cost



Notes: The dotted line is the IRF for the 1954:Q4–1970:Q1 period, the dashed line is the IRF for 1970:Q2–1984:Q2, and the solid line is the IRF for the post-1984:Q2 period.

Figure 5: Impulse response functions for debt



Notes: The dotted line is the IRF for the 1954:Q4–1970:Q1 period, the dashed line is the IRF for 1970:Q2–1984:Q2, and the solid line is the IRF for the post-1984:Q2 period.

B Data

I use U.S. data from NIPA-BEA, CPS-BLS, the FRED database, and the Flow of Funds accounts from the Federal Reserve Board for the period 1954:Q4–2006:Q4.

B.1 Data used in estimation

- *Growth rate of real per-capita gross value added by the nonfarm business sector.* Data on nominal gross value added are available in NIPA table 1.3.5. I have deflated such a series using the implicit price index from Table 1.3.4. I divide the new series by the civilian noninstitutional +16 (BLS ID LNU00000000) series to obtain per capita variables. The data provided by the BEA are annualized, so I divide by 4 to obtain quarterly values for the measures of interest.

- *Growth rate of real per-capita investment.* Investment is defined as the sum of personal consumption expenditures of durables and gross private domestic investment from NIPA table 1.1.5. I deflate the nominal variables using the GDP deflator provided by NIPA table 1.1.4. We weight the resulting series using the relative significance of the nonfarm, nonfinancial corporate business sector in total GDP.

- *Growth rate of real per-capita consumption.* Consumption is defined as the sum of personal consumption expenditures of nondurables and services from NIPA table 1.1.5.

- *Growth rate of net worth.* I consider data from the Flow of Funds Accounts data set constructed by the Federal Reserve Board. I define net worth (corporate net worth 2) as tangible assets (table B.102, line 2) minus credit market instruments at market value (table B.102, line 22) in the nonfinancial corporate sector.[5]

- *Hours worked* is defined as the log level of the hours of all persons in the nonfarm business sector provided by the BLS divided by 100 and multiplied by the ratio of the civilian population over 16 (CE16OV) to a population index. The population index is equal to the ratio of population in the corresponding quarter divided by the population in the third quarter of 2005. This transformation is necessary, as the series on hours is an index with 2005=100.

[5]The vintage for the Flow of Funds Accounts is March 2014.

- *Growth rate of real wages.* Real wages are defined as the real per-capita counterpart of compensation of employees provided by NIPA table 1.12. Total compensation is corrected by the relative size of the nonfinancial corporate sector.

- *Inflation* is defined as the log difference of the price index for gross value added by the nonfarm business sector (NIPA table 1.3.4).

- The *federal funds rate* is taken from the Federal Reserve Economic Data (FRED).

- *Credit spread (Baa-10y)* is defined as the spread of the Moody's seasoned Baa corporate bond yield corporate bond rate and the 10-year Treasury constant maturity rate. I consider the log of the gross quarterly counterpart.

B.2 Data used in the empirical evidence section

In addition to the series described previously, I also consider the following:

- *Corporate net worth 1* is defined as total assets (table B.102, line 1 from FOFA) minus total liabilities (table B.102, line 21 from FOFA) in the nonfinancial nonfarm corporate sector in the United States. It is defined in real per-capita terms.

- *Leverage 1* is defined as the ratio of credit market liabilities to corporate net worth 1.

- *Leverage 2* is defined as the ratio of credit market liabilities to corporate net worth 2.

- *Tobin q* is the ratio of the sum of equities (market value of equities outstanding, series with mnemonics FL103164103) and total liabilities to total assets.

- *Equity q* is defined as the equities-to-net-worth (measure 1) ratio.

- *Corporate bonds* is defined in real per-capita terms and it corresponds to line 26 of table B.102.

- *Net increase in credit market liabilities* is given by table F.102, line 40 from FOFA. This is the measure of credit used by Christiano, Motto and Rostagno (2014).

- *Net increase in corporate bonds* is given by line 43 in table F.102.

- *Equity payout*, in Jermann and Quadrini (2012) is defined as net dividends (table F.102, line 3) minus net equity issues (table F.102, line 39) of nonfinancial corporate businesses.

- *Corporate bond spread (Baa-Aaa)* is defined as the spread of the Moody's seasoned Baa corporate bond yield and the Moody's seasoned Aaa corporate bond yield. I consider the log of the gross quarterly counterpart. The data are available in the FRED database.
- *Credit spread (Baa-ffr)* is defined as the difference between the Moody's seasoned Baa corporate bond yield and the federal funds rate. I use the spread in gross quarterly terms and take logs.